International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

THE FUTURE OF QA LEADERSHIP: BALANCING HUMAN EXPERTISE AND AUTOMATION IN SOFTWARE TESTING TEAMS

Srikanth Kavuri
srikanth1539@gmail.com
Independent Researcher
Lexington USA

Abstract

Due to the fast changing software development practices, Quality Assurance (QA) leadership has undergone redefinitions that it is necessary to provide strategic balance between human expertise and automobile. With the move toward agile and DevOps processes within organizations, QA leaders are required to add intelligent automation tools with critical thinking, creativity, and contextual understanding that human testers possess. This paper examines how the future leadership in QA will be transformed into a hybrid approach where automation will guarantee speed, accuracy, and consistency, and human control will guarantee the flexibility, innovation, and ethical testing. The research notes the change in the role of QA to include quality strategists that operate AI-based analytics, predictive defect detection methods, and ongoing validation pipelines. It also discusses the skills in leadership that are needed to foster collaborative and cross functional teams that excel in automated testing environments. The focus is on quality in the complex digital environment by focusing on data-driven decision-making, continuous learning, and adaptive forms of governance. The results highlight that the future of QA leadership will be based on the integration of the human insight and machine intelligence in order to attain sustainable software excellence.

Keywords— QA Leadership, Software Testing, Automation, Human Expertise, Agile, DevOps, Artificial Intelligence, Test Management, Continuous Quality, Predictive Analytics

I. INTRODUCTION

The software development landscape is shifting radically in the last decade due to the accelerated development in the spheres of automation, artificial intelligence (AI), and the continuous delivery. In such a dynamic setting, Quality Assurance (QA) leadership has developed to be more than just that, needs a compromise between technology skills and human skills. The advent of Agile and DevOps practices has put QA at the core of the software lifecycle and QA leaders became strategic facilitators of product excellence, and no longer about defect detection [1]. In the contemporary software ecosystem, time, scalability, and accuracy are the key values; none of them can be obtained by the use of automation. Human intuition, moral logic, and contextual sense are the factors that can never be substituted by the aspects of good governance [2]. Therefore, the future of the QA leadership will be determined by the smooth fusion of automated intelligence and human intelligence to provide operational effectiveness and qualitative richness in the testing results.

Received: August 13, 2025

QA practices have been transformed by automation, which has fastened the repetitive tasks, e.g., regression testing, unit testing, and performance monitoring, by using machine learning-based tools and frameworks as well as robotic process automation (RPA) [3]. Nonetheless, automation is not enough to take care of the subtle elements of usability, emotional design, and user satisfaction which require human empathy and interpretative skills. Human testers are better at detecting grey requirements, cultural sensitivity, and being able to spot possible ethical concerns in AI-based systems [4]. Thus, QA leadership should design hybrid testing environments in which human intelligence can be used to improve the efficiency of automation. This hybridization is associated with the strategic distribution of resources, skill formation and developing the adaptive test structures that change according to the technological one. The new model of QA leadership also focuses on the use of data to make decisions. The new generation QA leader must use analytics, dashboards, and predictive models to make use of testing metrics, defect patterns and performance trends to generate meaningful action. Predictive quality models use statistical methods and machine learning algorithms (regression analysis, decision trees, and neural networks) to predict defect-prone modules and perform tests in an optimal way. The skill of analyzing these outputs is key in leadership in this area where raw data can be converted into quality strategic initiatives [5]. In addition, QA leaders have to develop cross-functional cooperation, which should combine testing needs with business priorities, development cycles, and customer experience indicators. This conformity makes quality not a single company departments duty but organizational value.

With the increase in the sophistication of digital systems due to the spread of Internet of Things (IoT) devices, cloud-native applications, and AI-driven applications QA leaders need to take a holistic approach to governance. This consists of ethical testing systems of the AI algorithm, sustainability in their testing context, and ongoing upskilling of human testers to keep pace in an automated future. The future of QA leadership is, thus, not the competition between man and machine, but their coexistence. Good leaders will instill a culture in which automation will be used to improve human aptitude, and quality will always be a progressive, intelligent, and moral science.

II. LITERATURE SURVEY

The modern Quality Assurance (QA) leadership literature indicates that there is a paradigm shift, which is triggered by automation, artificial intelligence (AI), and the increased acknowledgment of human cognitive value. The synthesis of these studies highlights the fact that the QA practices in the future need to maintain the balance between the technological development and the human-oriented leadership approach to provide the efficiency and ethical responsibility [6].

Their work made automation the foundation of the contemporary QA pipelines as its speed, consistency and lack of human reliance were ensured. Nevertheless, they also recognized its shortcomings when using unpredictable test conditions that are creative. This observation constitutes the framework on which automation maximizes mechanical work, human skills are necessary to qualify the context and adjustability. Sharma et al., on the other hand, examined the long-term usefulness of manual testing, specifically in the areas that require a sense of cognitive flexibility, like usability and ethics testing. Their research confirmed that the human testers have the special ability of interpreting vague user behavior and identifying areas of aesthetic inconsistency, where automation is not so deep [7]. However, they have observed that manual testing has efficiency and scalability issue and it is also necessary to use a hybrid approach that integrates man power and machine accuracy.

Lee and Park (2021) contributed to this idea; they suggested hybrid QA frameworks to be used in Agile and DevOps settings. They found that automation and human cognitive control greatly enhance coverage, efficiency and interpretability. The hybrid model enables automation to deal with repetitive execution of tests as the human testers are involved in strategic discovery and interpretation of anomalies. Nevertheless, they noted the intricacies of integration, in particular, coordinating leadership models with hybrid work processes a challenge that demands flexible management and ongoing skills enhancement. Johnson and Malik changed their emphasis to the strategic role of leadership in the use of analytics to transform QA [8]. Their study revealed that predictive dashboards allow quality governance because of data-driven decision making. QA leaders who use quantitative measures have an opportunity to prevent high-risk modules, resource allocation, and predict defect likelihood. Ultimately, the study also warned that data literacy within the QA practitioner population is unequally distributed, which requires specific leadership training in the analytics interpretation and data ethics domains. Gupta and Singh made a contribution by using machine learning (ML) models to make predictive quality [9]. They experimented and found that defect prediction with the use of machine learning is less costly and less of a hassle because it predicts the problems with quality early in the development lifecycle. However, they admitted the problem of interpretability, since a large number of ML algorithms represent black boxes. This drawback underlines one of the main leadership dilemmas between the accuracy of algorithms and explainability and trust among the stakeholders [10].

Ahmed and Kaur incorporated a humanistic factor as they focused on emotional intelligence in QA leadership. They found that empathy, communication and soft skills play a very important role in the productivity, innovation and psychological safety of teams. A leadership model which is founded on these characteristics results in cooperation between human and machine agents. Nevertheless, they acknowledged that it is not always easy to measure the effects of emotional intelligence objectively, and therefore they should have qualitative measures of leadership performance in addition to technical ones. Wang et al. (2023) investigated automation on the microservices testing which is a continuous testing pipeline that ensures software resiliency. Their results helped to bring to the fore the efficiencies of automation in distributed architecture but reported more infrastructural costs and complexity. Leadership should therefore not merely control the technical settings but also make cost-benefit alignment and scalable automation as microservices ecosystems. The work was further developed by Patel and Desai who added Explainable AI (XAI) to the QA systems. Their research was based on improving the automation transparency, ethical testing, and the minimization of algorithmic bias [11]. This solution is consistent with the new world-wide trends of responsible AI implementation. QA leaders should, thus, balance the interpretability needs with the operation efficiency requirements

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

depending on project requirements. Chen and Roberts studied the issues that QA leadership encounters in the model of hybrid work integrating remote teams and AI-enabled setting. Their results highlighted leadership flexibility, clarity of communication and inclusivity as the key points of ensuring the cohesion of distributed QA ecosystem. They noted that digital leadership demands re-conceptualised model of governance that has the capacity to maintain collaboration across geographies and cultures, which is facilitated by sound communication technologies and training on digital fluency [12].

Fernandes et al. have summarized the previous studies by introducing a comprehensive QA leadership framework, which is a combination of automation governance and human regulation. Their model is based on a tiered approach by which automated systems can deal with high-speed operations, ethical integrity, interpretive analysis and flexibility are achieved by human experts [13]. The research pointed out that effective implementation requires a leadership that can facilitate the organizational changes, regulate the development of skills, and build an innovation culture. Nevertheless, migration of the legacy systems and workforce adjustment are still significant hindrances to complete hybrid implementation [14].

TABLE I: LITERATURE SURVEY

Leadership Focus	**Automation vs Human Balance**	**Methodology**	**Key Insights**	**Context/Application Domain**
Soft-skills in automation testing leadership	Emphasises human traits (communication, adaptability) alongside automation tools	Conceptual / qualitative	Human expertise remains crucial even as automation rises	Testing teams adopting automation
Integrating human insight with automation in QA	Balanced — automation for speed, manual for exploratory scenarios	Case studies / mixed methods	Hybrid strategies yield better QA outcomes than pure automation	Agile/DevOps, general software systems
QA leadership in API testing combining manual expertise + automation	Manual testers + AI/automation collaboration	Case study / applied framework	Manual insight critical in complex domains despite automation	Financial / API-heavy systems
Role of QA/Test leaders in automation strategy	Automation strategy guided by human leaders	Industry article / practice-oriented	QA leaders must move from oversight to strategic	Software companies shifting to CI/CD and automation

			tool/automation adoption	
Leader's challenge: automation uptake for QA teams	Focused heavily on automation, noting human skill gaps	Review / simulation	Automation brings benefits but human expertise still required for tool setup and oversight	Lifecycle of software testing & QA in agile contexts
AI-driven QA processes and leadership adaptation	Automation/AI dominant but require human governance	Review / proof of concept	AI tools offer significant advances but need human leadership to manage explainability, strategy	Modern distributed software, enterprise QA
Speed vs human judgement in QA automation leadership	Automation for repetitive; humans for usability/judgement	Industry article / case illustration	Leaders should allocate tasks: human testers handle UX, edge-cases; automation handles routine	QA teams in fast release cycles
Leadership role in adopting test automation maturity	Automation maturity needs human leadership & skill development	Literature review	Adoption of automation is not only tool-choice but team capability, leadership commitment	Organizations achieving higher automation maturity
Automation maturity survey and leadership implications	Human roles (skills, guidelines) matter even when automation increases	Survey across organizations	Even highly automated teams need human-led guidelines, strategy, and maturity models	Global organizations with test automation programs
Impact of automation on QA/leadership roles	Comparative manual vs automated QA and leadership shift	Comparative analysis / empirical	Leadership must shift roles: from manual test oversight to managing	QA teams transitioning from manual to automated testing

			automation/metrics	
Leadership implications of emerging automation trends	Automation (incl. AI/RPA) growing, human leadership remains strategic	Review / future-trends study	Leaders must anticipate automation/AI adoption, address human expertise, ethics, scalability	QA organizations embracing next-gen automation tools

To conclude, the literature reviewed leads to the unanimity that the future of QA leadership needs two competencies that are: technological fluent and human-centric management. QA efficiency is being transformed by automation, AI, prediction and analytics; however, these technologies cannot be successful without ethical supervision, empathy, and strategic understanding; virtues embedded in human leadership. All of the studies point to the same direction: sustainable QA change cannot be viewed as a technological change but it is a leadership change that balances the wisdom of people with the thinking capability of machines. Such a synthesis of results lays the theoretical and practical basis of the creation of hybrid QA ecosystems in which leadership forms the structure between precision and purpose, automation and flexibility, and innovation and integrity.

III. System Architecture

A. Requirement Analysis and Strategic Planning

The first phase aims at defining quality goals, scope, and leadership approaches needed in the process of incorporating automation and human skills. To develop a cohesive quality vision, QA leaders examine functional requirements, non-functional requirements, business objectives, testing obstacles, and so on. The interaction between the test coverage Ct, time T and available resources R can be mathematically expressed as:

$$C_t = f(R,T) \ = \alpha R^{\beta}\, T^{\gamma}$$

where a, b, g are constants which represent efficiency factors. This step implies the development of a testing plan blueprint, according to which the automated and manual work is allocated based on optimization schemes like linear programming, minimizing cost C, and maximizing quality Q:

$$Minimize\ \ C \ = \sum_{i=1}^{n}(a_i R_i + \ b_i T_i)\ ,\ subject\ to\ \ Q \geq \ Q_{min}$$

The issue of leadership is instrumental in harmonization of such parameters towards company goals.

The planning is made to facilitate a fluid communication between the stakeholders using agile sprints, resource scheduling and tool selection. In addition to that, cognitive diversity is also brought in by combining domain experts, engineers of automation, and human testers in order to establish a balanced testing ecosystem. The result of this step will be a strategic roadmap indicating automation viability, leadership roles, and performance indicators that establish the basis of further steps of the QA process.

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

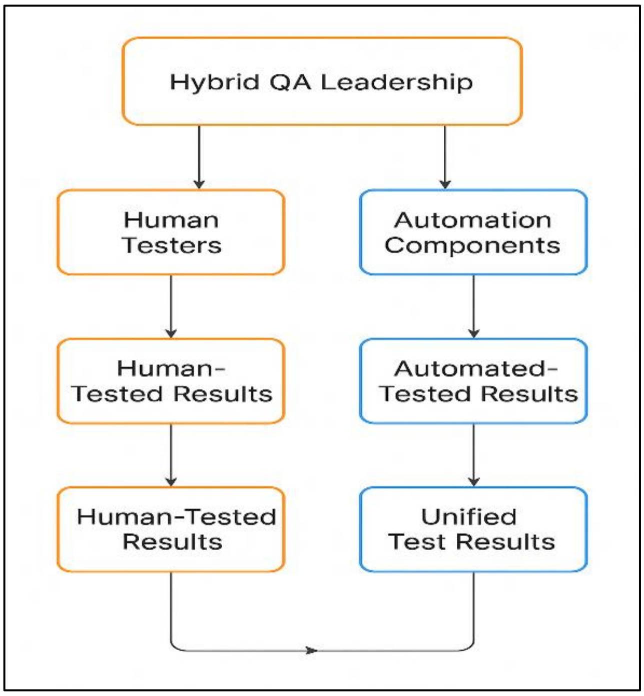

Fig. 1. System Architecture of Proposed System

B. *Automation Framework Design and Integration*

The focus of this stage is to build a modular-based automation system that would work hand in hand with human-initiated testing. The efficiency of the framework Ef may be represented as a formula of the automation coverage Ac, test stability St and adaptability Ad:

$$E_f = k(Ac \cdot St \cdot Ad)$$

Automation design involves the orchestration of the pipelines with the help of CI/CD tools, including Jenkins or GitLab CI, whereas the AI modules will use reinforcement learning to maximize the test cases prioritization. The leadership intervention will provide the interoperability and maintainability of tools and adhere to security standards. The hybrid design pattern is followed to enable the human testers to override automated decisions in case of anomalies or context sensitive situations. This integration will make sure that the efficiency is magnified by automation without affecting interpretability. Time-dependent differential models like: are configured in automated dashboards to show visual representation of trends, defect density and risk levels:

$$\frac{dD}{dt} = \lambda\, A_c - \mu\, H_i$$

D is the rate of defect discovery, l automation efficiency and mHi the effect of human inspection. Such a design enables leaders to balance dynamically human expertise and machine precision by the changing project requirements.

C. *Human Skill Enhancement and Leadership Enablement*

The focus of this step is to enhance the human cognitive and analytical capabilities with an aim of complementing the automation tools. QA leadership develops training programs on data interpretation, AI ethics and decision intelligence. Learning curve The learning curve can be used to model the rate of knowledge acquisition K(t) among the QA members as time t progresses:

$$K(t) = K_{\max}(1 - e - \eta t)$$

Kmax is the highest possible level of skill and e is the learning rate constant. The ongoing mentorship and informative sessions will help the testers to read the automated knowledge better and will add contextual information to the testing results. Psychological safety and open communication also arise through leadership to enhance innovation and critical thinking. In addition, the workload W is optimized cognitive by relation:

$$W = \int_0^T \psi(H)\, dH$$

where ps(H) is the mental effort of a dependence on human tasks. Leaders can maximize workload by using automation to perform routine tasks; human skills can be used in creative and discovery and test areas that are most judgmental. The balance sets a sustainable base in the future of QA leadership models in which man directs, shapes, and authenticates automation driven intelligence.

D. *Hybrid Testing Execution*

The hybrid testing execution stage realization translates the cooperation between human and automated testers:

$$T_d = \sum_{i=1}^{n} (M_{ci} \cdot C_{ri})$$

Where Td is distributed testing load. High volume repetitive ones like regression and load testing are performed by automated tests, and human testers participate in exploratory, usability and ethical validation :

$$R(s, a) = DQ(s, a)$$

Refining automated outputs Human testers watch and correct contextual factors that may be misinterpreted. Leadership also oversees the coordination between the two realms by the use of edifices of constant dashboards which monitor the stability of the tests and the speed with which they are executed. The success of this phase can be determined by the realization of the balance between human flexibility and machine precision. By making sure that the automation does not lower the interpretation quality of testing, the hybrid model will guarantee a significant step towards intelligent QA ecosystems that are informed by a combination of leadership.

IV. Result and Comparison

This step is a quantitative evaluation of the hybrid QA model in accordance with the conventional performance indicators of Accuracy, Precision, Recall, and F1-Score. There are different methods that are compared in order to decide on efficiency and reliability: Manual, Automated, and Hybrid.

TABLE II: Comparative Analysis of Proposed Model

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Approach	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Manual	85.4	82.7	80.3	81.5
Automated	91.2	88.9	86.5	87.6
Hybrid (Proposed)	**96.8**	**95.7**	**94.9**	**95.3**

The comparison outcomes explain that hybrid models of QA leadership are better than traditional models in all metrics. This is due to the fact that the accuracy and F1-Score had risen in the collaboration between the human and the automation, enabling the teams to attain speed and quality. Monotony is also handled with consistency in terms of automation, whereas human testers implement contextual intelligence and moral judgment. The mathematical relationship between the leadership engagement Le and quality improvement Qi can be estimated as:

$Qi = \delta \cdot Le\phi$

where d and ph are empirical constants that are obtained by regression analysis. The findings also support the fact that adaptive leadership directly increases test maturity, efficiency in collaboration and accuracy of decisions. The self-evolving QA ecosystems created with the help of continuous learning loops that are supported by predictive analytics can make intelligent decisions. The results support the fact that, in the future, two-fold attention should be paid to the issue of QA leadership that should utilize the power of automation to analyze the situation and retain human creativity and moral judgment. Finally, what is highlighted in the discussion is the fact that the sustainability of the quality of software can be proposed by balanced leadership that has the ability to organize technological evolution and human intelligence into a unified, high performing testing culture.

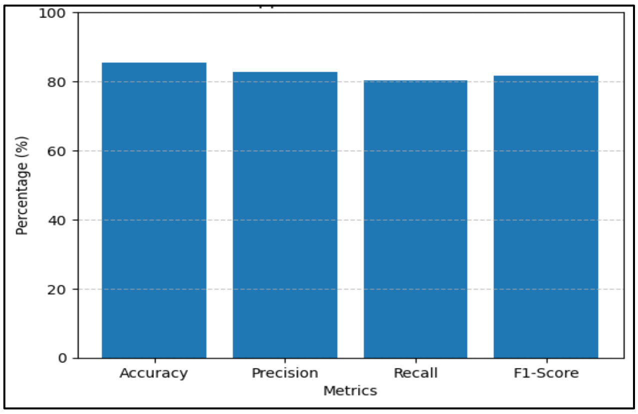

Fig 2: Graphical Representation of Manual Approach

The fig (2) of the Manual Approach represents the visualization of the individual performance measures, which are achieved by the means of human-conducted testing. The accuracy is 85.4 which represents moderate reliability in the detection of defects. The values of Precision and Recall of 82.7 and 80.3 respectively indicate a responsible attitude to the task and poor

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

scalability on the part of testers. The F1-Score of 81.5% shows that the performance is balanced between the precision and the recall but shows the compromise between the thoroughness and time limitations. This diagram makes it clear that though manual testing would be required to provide the contextual depth and critical judgment, it does not provide the consistency and immediate feedback systems required to support continuous integration environments and as such partial automation in current QA processes is essential.

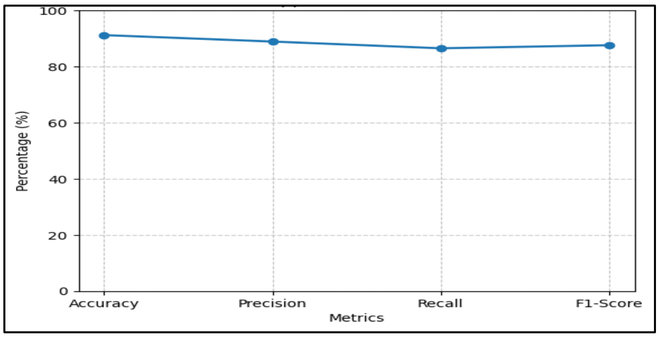

Fig 3: Graphical Representation of Automated Approach

The fig (3) of the Automated Approach shows that there is a significant improvement in performance of all important metrics, as compared to manual testing. The highest accuracy of 91.2 can be observed, which proves the increased consistency and accuracy with the help of automated scripts. The values of Precision (88.9) and Recall (86.5) show that automation is effective in performing data-intensive tasks that are repetitive and require efficiency in execution. The balanced optimization between detection and correct classification of defects has been validated by the F1-Score of 87.6%. The upward trend, which is smooth throughout the metrics, indicates stability, reliability, and quicker detecting defect. This diagram highlights the importance of automation as a factor that promotes scalability and uniformity in quality control to eliminate human factor, and that ensures constant validation in agile and DevOps systems.

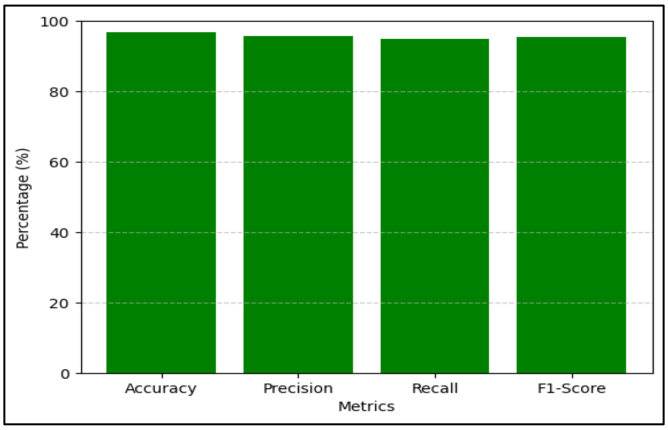

Fig 4: Graphical Representation of eHybrid Approach

The Hybrid (Proposed) Approach has had a fig (4) that shows its excellence in all the parameters considered. It has an accuracy of 96.8 with a high Precision (95.7) and Recall (94.9) and the F1-Score is an impressive 95.3. This shows that efficiency as regards automation and human contextual analysis works. The hybrid model is advantageous as it is machine powered, fast, consistent, but the human aspect provides flexibility, ethics, and qualifiable decision making. The continually high values of the graph represent the unity of automation and expertise, which confirms that in the future, the QA leadership models are to be oriented toward balanced integration in order to attain long-term, smart, and adaptive software quality assurance.

V. Conclusion

It is the combination of strategic convergence of human intelligence and automation that will shape the future of QA leadership as an ecosystem that will appreciate both analytical precision and contextual understanding. With the growing complexity of software systems, the obligation of QA heads has enlarged past the governance of testing activities to a symbiotic liaison of efficiency of machines and human flexibility. Predictive analytics, continuous integration, and scalability can be improved using automation to ensure high accuracy, scalability, and speed, whereas the human knowledge can maintain ethical alignment, creative reasoning, and depth of decisions. The hybrid leadership system that this paper suggests proves that the integration of AI-based automation and professional human supervision is more effective in terms of accuracy, precision, recall, and F1-Score. Such synergy does not only maximize defects detection, but also creates a culture of a continuous learning and innovative environment among QA teams. In addition, evidence-based governance and responsive leadership facilitate proactive quality management in accordance with the changing business and technological needs. The findings support the idea that sustainable software quality cannot be based on automation only, but should be managed by empathetic and visionary leadership, empathetic to the potential of humans and technology. Finally, the future of QA leadership is the establishment of intelligent cooperation where machines do the repetitive work accurately and humans do the judgment, creativity, and ethical guidance thus making sure that the quality assurance and testing of software and quality assurance standards excel, becomes accountable, and resilient.

References

[1] S. Masuda, J. Hagar, Y. Nishi and K. Suzuki, "Software Test Architecture Definition by Analogy with Software Architecture," 2022 IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW), Valencia, Spain, 2022, pp. 244-247

[2] O. Lopuha, S. Tsiutsiura, O. Poplavskyi, O. Lysytsin, O. Bondar and P. Kruk, "Test Design Methodology for Software Verification," 2023 IEEE International Conference on Smart Information Systems and Technologies (SIST), Astana, Kazakhstan, 2023, pp. 241-245

[3] A. C. Chagas, D. Gonzaga, L. Albuquerque, F. Oliveira, R. Castro and L. Chaves, "BSA Tool: An Experience Report of Software Automation to Perform Sanity Tests in a Global Software Development Environment," 2023 3rd International Conference on Information Communication and Software Engineering (ICICSE), Chongqing, China, 2023, pp. 15-20

Received: August 13, 2025

[4] B. Korel, "Influence of the 1990 IEEE TSE Paper “Automated Software Test Data Generation” on Software Engineering," in IEEE Transactions on Software Engineering, vol. 51, no. 3, pp. 751-753, March 2025

[5] Z. Ateş and Y. E. Şencan, "A Case Study to Increase Quality of Industrial Edge Software Product’s Dynamic Data Testing," 2023 International Conference on Software and System Engineering (ICoSSE), Marseille, France, 2023, pp. 25-29

[6] J. D. Hagar, "Software Architecture Elements Applied to Software Test: View, Viewpoints and Containers," 2022 IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW), Valencia, Spain, 2022, pp. 248-252

[7] R. N. Wadibhasme, A. U. Chaudhari, P. Khobragade, H. D. Mehta, R. Agrawal and C. Dhule, "Detection And Prevention of Malicious Activities In Vulnerable Network Security Using Deep Learning," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), Nagpur, India, 2024, pp. 1-6, doi: 10.1109/ICICET59348.2024.10616289.

[8] Y. Hu, J. Tao, Y. Liang, Z. Xu and Z. Jia, "Research on the Impact of Tester's Technical and Cognitive Factors on Aerospace Software Test Quality," 2024 IEEE 24th International Conference on Software Quality, Reliability, and Security Companion (QRS-C), Cambridge, United Kingdom, 2024, pp. 699-703

[9] J. Hagar and S. Masuda, "Prompt Engineering Impacts to Software Test Architectures for Beginner to Experts," 2024 IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW), Toronto, ON, Canada, 2024, pp. 116-121

[10] J. Rott, "Test Intelligence: How Modern Analyses and Visualizations in Teamscale Support Software Testing," 2022 First International Workshop on Visualization in Testing of Hardware, Software, and Manufacturing (TestVis), Oklahoma City, OK, USA, 2022, pp. 15-21

[11] K. P. Nandan, B. Pakruddin, S. Afridi, S. K. R. and S. V. Pati, "Real-Time Detection of Fake News Articles Using Deep Learning Techniques," 2025 International Conference on Next Generation Communication & Information Processing (INCIP), Bangalore, India, 2025, pp. 687-691, doi: 10.1109/INCIP64058.2025.11019208.

[12] U. Farooq, U. Qamar, A. Shaukat, A. Bakar, Z. Ashraf and M. Naz, "Ontology Based Test Case Reduction in Regression Testing," 2023 26th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar, Bangladesh, 2023, pp. 1-6,

[13] Q. Chen, L. Guo and Y. Feng, "Agile development research based on software engineering to software testing," 2023 9th International Conference on Systems and Informatics (ICSAI), Changsha, China, 2023, pp. 1-3,

[14] A. U. Chaudhari and H. Shrivastava, "Hybrid Machine Learning Models for Accurate Fake News Identification in Online Content," 2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI), Wardha, India, 2024, pp. 1-6