Factors affecting the adoption of AI-driven automation within DevOps practices among IT professionals in Sri Lanka

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ABSTRACT

This research explores the factors influencing the adoption of AI-driven automation within DevOps practices among IT professionals in Sri Lanka. Drawing on a conceptual framework that integrates technical, strategic, and organizational dimensions, the study examines how four key constructs—technical Enablers (access to AI tools and efficiency gains), Future Focus (strategic orientation toward AI expansion), Barriers (cost, skills, integration complexity), and Organizational Readiness (culture and change-management support)—relate to the degree of AI adoption in CI/CD pipelines, automated testing, and real-time monitoring.

A quantitative survey was administered online to a stratified sample of 384 respondents across job roles (developers, DevOps engineers, QA Engineers, project managers) and organization sizes. Items were measured on five-point Likert scales and organized into five sections: Demographics, Enablers, Future Focus, Barriers, and Organizational Readiness, plus a direct measure of Adoption Level. Data were analyzed using IBM SPSS: reliability testing (Cronbach's alpha) confirmed internal consistency; exploratory factor analysis validated the measurement structure; Pearson correlation assessed bivariate relationships; and Hayes' PROCESS macro tested mediation (Future Focus) and moderation (Organizational Readiness) hypotheses.

By combining robust statistical methods with a multi-dimensional conceptual model, this study provides insights into the mechanisms through which AI capabilities, strategic planning, and organizational context drive or inhibit the integration of AI into DevOps workflows in emerging-economy settings.

Keywords: AI-driven automation, DevOps adoption, Organizational readiness, Technology enablers, Adoption barriers, Future focus, Sri Lankan IT sector

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1. Introduction

In the modern digital economy, software development teams have never had to work harder to quickly develop strong, safe, and scalable programs than they do now. As companies try to come up with new ideas and respond to change faster than their competitors, the efficiency of software development and deployment pipelines has become a critical factor in success. DevOps is a collaborative approach that integrates software development (Dev) with IT operations (Ops). It has become an important aspect of modern software engineering approaches because of these limitations. DevOps breaks down the walls that used to separate teams, encourages continuous integration and delivery (CI/CD), and fosters a culture of working together, automating, and taking responsibility for the whole life cycle of an application. But even DevOps approaches are being stretched to their limits as software delivery gets more complicated and faste.

A new approach to address these challenges is AI-powered automation in DevOps. AIOps, which is a combination of AI and DevOps, promises to give DevOps teams greater power by integrating smart decision-making, predictive insights, and self-healing mechanisms into the software development lifecycle. AI-powered technologies can help DevOps operate better in a number of ways, such as by automating operations that need to be done over and over, making code reviews easier, detecting performance bottlenecks, predicting deployment problems, optimising resource allocation, and making testing more accurate. For instance, machine learning algorithms can discover problems in deployment data or logs in real time, which allows you to correct them before they arise

AI-enhanced CI/CD pipelines may adapt to what the system tells them, and AI-powered automated testing frameworks can make tests more complete and accurate. Even while these are clear benefits, not all DevOps teams are utilising AI-powered automation. In countries like Sri Lanka, many IT organisations are still in the early stages of testing. Some have only partially integrated AI into some tasks, while others are unsure or don't want to use it. There are many reasons why this gap in adoption exists, but the reasons haven't been discovered yet.

1.1 Background

Despite these clear benefits, the adoption of AI-driven automation in DevOps is not uniform. In regions like Sri Lanka, many IT organizations are still in the early stages of experimentation, with some having partially integrated AI into specific processes and others remaining uncertain or resistant to adoption. The underlying reasons for this variation in adoption are multifaceted and not yet fully understood.

DevOps has become a mainstream operating model for software delivery, coupling continuous integration and delivery (CI/CD) with culture, automation, and measurement to accelerate release cadence and improve system reliability. In parallel, organizations are increasingly experimenting with AI-driven automation (often framed as “AIOps”) to enhance testing, monitoring, change risk analysis, and resource optimization. Yet, despite strong vendor momentum and market growth forecasts for AIOps, the empirical evidence that AI already improves software delivery outcomes at scale is mixed. The 2024 DORA/Google Cloud State of DevOps report [6], for example, finds that using AI tools is not yet consistently associated with higher software delivery performance, cautioning that adoption value is context-dependent and process-sensitive rather than automatic.

A study applying the Technology-Organization-Environment framework revealed that while high-quality data and perceived advantages drive AI adoption, low top management commitment acts as a barrier, reflecting leadership gaps in AI strategic alignment [20]. Moreover, research on DevOps adoption in Sri Lanka highlights organizational culture issues, skill gaps, resistance to change, and lack of visionary leadership as major obstacles to effective implementation [21].

Empirical studies in financial institutions demonstrate that integrating AI with DevOps, particularly for real-time applications like fraud detection, can enhance operational efficiency but is impeded by data quality issues, model interpretability concerns, organizational resistance, and regulatory compliance burdens [23]. This collective evidence underscores a critical research gap on practical AI-DevOps integration in Sri Lanka's evolving digital ecosystem, justifying investigation into tailored organizational strategies and institutional capacity building to overcome these multifaceted challenges.

This research is motivated by the urgent need to understand the factors that influence the adoption of AI-driven automation in DevOps, Global tech giants are setting the rules for how to employ AI, but for many small and medium-sized firms, things are not the same. They can't employ AI because they don't have the necessary tools and budget, they don't have enough skilled workers, they can't finance it, and their companies are reluctant to change.

On the other hand, having mature AI technologies, support from leadership, an organisation that can adapt quickly, and obvious efficiency gains are all key for making it simpler to implement AI. These things make it easier for companies to initiate or grow the usage of AI in DevOps workflows. On the other hand, things like high implementation costs, not having the right technical skills, the difficulty of integrating new tools, and the fact that tools are spread out might make adoption take a long time or even stop it completely. For the simplicity study identify factors as follows ,

Enablers such as the availability of mature AI tools, leadership support, organisational agility, and demonstrable efficiency gains play a critical role in facilitating AI adoption.

Barriers such as high implementation costs, limited technical skills, integration complexity, and tool fragmentation can significantly delay or prevent adoption.

But just talking about enablers and barriers doesn't tell the complete story. Companies don't employ AI just because there are tools for it, and they don't avoid it just because it costs too much.

Future Focus. Future Focus reflects an organization’s orientation toward technological innovation, its plans to expand AI usage, its proactiveness in seeking The organisation is focused on new tools, believes in AI as a critical enabler for DevOps success, and recognises the need for clear standards and best practices. This strategic focus serves as a mediator between practical enablers and actual adoption decisions. Additionally, the impact of barriers may vary based on,

Organisational Readiness. Organisations that exhibit strong change management, supportive cultures, and executive alignment are better equipped to overcome barriers. In other words, organisational readiness acts as a moderator, weakening the negative effects of barriers to adoption outcomes.

1.2 Problem statement

Despite the growing promise of artificial intelligence to automate and optimize software delivery, its integration into DevOps practices remains inconsistent, particularly in emerging‑economy contexts like Sri Lanka. While global leaders report significant gains in deployment speed, error reduction, and system reliability through AI‑driven tools, many Sri Lankan IT organizations struggle to translate technical capabilities into sustained adoption. Constraining factors include high implementation costs, limited AI‑DevOps skills, and the complexity of integrating new platforms into established CI/CD pipelines. Simultaneously, even organizations with access to advanced tools often lack the strategic vision and change‑management frameworks necessary to leverage these capabilities effectively. Without a clear understanding of how technical enablers, strategic orientation, perceived barriers, and organizational readiness interact to shape adoption outcomes, practitioners cannot confidently invest in or scale AI‑driven automation. This research addresses that gap by empirically modeling the mediating role of strategic “Future Focus” and the moderating role of organizational readiness in Sri Lankan IT professionals’ adoption of AI‑driven DevOps.

1.3 Research Objectives

This study aims to provide a clear picture of how AI‑driven automation is being adopted in DevOps by IT teams in Sri Lanka, identifying both the practical opportunities and the obstacles organizations face. By surveying professionals across different roles and company sizes, it will reveal how readily available AI tools translate into real‑world use, what holds teams back. whether it’s cost, skill shortages, or integration challenges—and how a supportive culture and leadership mindset can help overcome those hurdles. Ultimately, the research will offer concrete, easy-to-apply recommendations for IT leaders and decision-makers on how to align technology investments, planning processes, and organizational practices to accelerate and sustain the successful integration of AI into their DevOps workflows.

- Analyse the Challenges faced when adopting AI in to DevOps
- Asses the how AI has adopted into Automation in Sri lankan context
- Assesses organisational readiness to accept the and adopt the AI into automation.
- Factors that drive AI adoption and what factors hinders the adoption of AI in to DevOps

1.4 Research Scope

This research focuses specifically on AI‑driven automation within DevOps practices among IT professionals in Sri Lanka. It examines how companies of various sizes and roles like developers, DevOps engineers, QA enginners, and managers are integrating AI into key areas like CI/CD pipelines, automated testing, and real-time monitoring. The study measures the availability and use of AI tools, the barriers organizations face (e.g., cost, skills, complexity), and the cultural and leadership factors that support or hinder adoption. By concentrating on this emerging-economy context, the research delivers insights that are both locally relevant and broadly applicable to similar markets exploring AI in software delivery.

1.5 Research Gap

Although DevOps and AI have each been studied extensively, there is a lack of empirical, quantitative research examining how AI‑driven automation actually takes hold in real‑world DevOps workflows. especially within emerging‑economy contexts such as Sri Lanka. Prior studies tend to focus on case examples or theoretical potential, with little systematic data on the extent of adoption, the distinct obstacles organizations face, or the strategic and cultural factors that enable or inhibit progress. Moreover, existing research rarely integrates both a strategic orientation ("Future Focus") and an organizational readiness perspective into a unified model explaining adoption outcomes. This creates a critical gap: without understanding how technical capabilities, forward‑looking planning, and internal change-management capacity interact, IT leaders cannot develop targeted interventions to move beyond pilot experiments and achieve sustained, scalable AI‑DevOps integration.

Outline

The thesis opens with Chapter 1 (Introduction), which frames the rise of AI in DevOps, defines the uneven adoption problem in Sri Lanka, and sets out the study's aims. Chapter 2 (Literature Review) then surveys DevOps principles, AI‑driven automation, their intersection, global versus emerging‑market trends, industry‑specific insights, and the research gap. Chapter 3 (Methodology) describes the quantitative survey of Sri Lankan IT professionals, details the sampling and instrument design, and explains the statistical procedures, reliability testing, exploratory factor analysis, correlations, and mediation/moderation models. Chapter 4 (Results) presents descriptive statistics, reliability metrics, factor analysis outcomes, correlation results, and the mediation and moderation analyses. Chapter 5 (Discussion) interprets these findings relative to existing theory, explores theoretical and practical implications, acknowledges limitations, and proposes future research. Finally, Chapter 6 (Conclusion & Recommendations) synthesizes the contributions and offers concrete guidance for practitioners and policymakers to foster sustainable AI adoption in DevOps.

2. Literature Review

The study looks at Sri Lankan IT professionals, who are a technology rich yet underexplored population. The digital sector in Sri Lanka is growing, and people are more interested in AI and DevOps. But a lot of organizations still have trouble using new technologies because of problems with their structure and strategy. This study try gets a lot of various comments from professionals in many fields, such developers, QA engineers, DevOps specialists, project managers, and operations staff. The idea is to add something to both theory and practice. In principle, integrating mediation and moderation techniques into adoption models helps us better understand how AI is employed in DevOps. In practice, it gives decision-makers vital information on how to move over problems, prepare for the future, and increase preparedness. This speeds up the process of adding AI to their DevOps pipelines.

In summary, this research aims to contribute both theoretically and practically. Theoretically, it advances our knowledge about AI adoption in DevOps by integrating mediation and moderation mechanisms into adoption models. Practically, it provides decision-makers with actionable insights into how to enhance readiness, focus on the future, and overcome barriers, thus accelerating AI integration in their DevOps pipelines.

2.1 DevOps: Principles and Role in the SDLC

Software engineering has long strived to make the different stages of the software development lifecycle (SDLC) fit together better. People used to think that software development and operations were two different realms. It was the job of developers to write code, and it was the job of operations teams to deploy and keep it running. This occasionally caused delays, confusion, discrepancies, and places that weren't always the same.

DevOps is a new method of doing things that seeks to fix these issues by combining development and operations into one flexible and automated way to deliver software. DevOps is more than just a collection of tools or steps. It is a change in culture that puts a lot of emphasis on working together, automating tasks, and always growing better. The fundamental purpose is to help companies make software that is faster, more reliable, and lasts longer [3], [4].

DevOps is founded on ideals that promote openness, flexibility, and quick reactions at every stage of the software development life cycle (SDLC). CALMS, which stands for Culture, Automation, Lean, Measurement, and Sharing, is one of the primary ideas behind DevOps.

The DevOps framework is based on the following principles. Culture encourages open communication and shared responsibility between development and operations teams. Automation reduces manual work and speeds up delivery by streamlining build, test, and deployment pipelines. Lean focuses on eliminating waste and improving value creation through iterative feedback loops. Measurement encourages the use of metrics and observability tools to guide decision-making and continuous improvement; Sharing encourages knowledge exchange, collaboration, and trust among cross-functional teams.

Within the SDLC, DevOps plays an integrative role across multiple phases:

1. Planning: DevOps promotes collaboration during planning by including operations input early in the decision-making process, ensuring that infrastructural and deployment considerations are part of the initial design.

2. Development: Code is developed using version control systems, and best practices such as code reviews, unit test automation, pair programming, and static analysis are emphasized. Automation tools ensure adherence to coding standards and facilitate early feedback.

3. Build and Integration: Continuous integration (CI) pipelines automatically compile, test, and package code upon each commit, reducing integration problems and enabling faster iterations.

4. Testing: Automated testing frameworks run unit, integration, and system tests, ensuring consistent quality. Test environments are provisioned using Infrastructure as Code (IaC) to maintain parity with production.

5. Release and Deployment: Continuous delivery (CD) pipelines automate deployment to staging and production environments. Techniques such as blue-green deployments, canary releases, and feature toggles minimize risk and downtime.

6. Operations and Monitoring: DevOps emphasizes real-time monitoring, alerting, and logging to ensure systems are observable. Post-deployment performance is tracked, and insights feed back into future development cycles.

The SDLC works much better with DevOps. Reports like the DORA State of DevOps reveal that DevOps teams that do well have shorter lead times, fewer changes that go wrong, and recover from problems faster. These improvements are not solely due to automation. They're also a lot about how individuals do their jobs and how the organisation is set up.

DevOps also encourages the use of Agile approaches, which focus on obtaining feedback from clients all the time and delivering in tiny chunks. DevOps expands on Agile by making sure that delivery and deployment are part of the iterative cycle. This brings development and operations closer together.

2.2 AI-Driven Automation in DevOps

Automation is becoming a big aspect of software engineering since software systems are getting more complex. DevOps already puts a lot of emphasis on automating testing, deployment, monitoring, and CI/CD pipelines. But adding AI to these DevOps tasks makes them even harder to understand. It helps systems not just do things automatically but also learn, adapt, and get better over time.

This transformation, which is called AI-driven automation in DevOps or AIOps, is the next stage in making software delivery work better. AI-driven automation combines a variety of tools, like machine learning (ML), natural language processing (NLP), and predictive analytics, to make software development and operations faster and more precise. These tools can search through vast volumes of code, logs, and telemetry data to detect problems, forecast when things will go wrong, and propose what to do. AI-enhanced solutions are distinct from regular automation tools since they can change, know what's going on around them, and learn from their failures [16], [10], [20].

In the context of DevOps, AI contributes significantly in the following domains,

1. Continuous Integration and Deployment (CI/CD): AI tools enhance CI/CD by detecting faults early, managing test pipelines more efficiently, and optimizing build-deploy cycles. According to Nagaraju et al. [12], AI has disrupted traditional CI processes by automatically scanning code for bugs, recommending fixes, and improving overall code quality through real-time suggestions and error prediction [12].
2. Automated Testing: Machine learning algorithms can automatically generate test cases based on historical bug data and usage patterns. This not only reduces manual testing effort but also enhances test coverage. Tools can also prioritize tests based on risk and impact, ensuring that critical functionality is always verified first.
3. Intelligent Monitoring and Incident Management: AI can monitor logs and metrics in real time to detect performance anomalies, forecast potential system failures, and even initiate auto-remediation workflows. As highlighted by Alter Solutions (2025). [1], predictive analytics and anomaly detection are enabling DevOps teams to move from reactive issue resolution to proactive system optimization.

4. Code Review and Quality Assurance: AI tools like GitHub Copilot, Tabnine, and DeepCode are revolutionizing code review by suggesting snippets, identifying

potential vulnerabilities, and enforcing coding standards in real-time. This has proven particularly useful in high-velocity environments where manual reviews may be time-constrained.

5. Security Automation (DevSecOps): AI-powered security scanners and threat detection systems can automatically identify vulnerabilities during the development lifecycle, helping enforce compliance and reduce security risks. With the rise of DevSecOps, integrating AI into security pipelines ensures that threats are mitigated early in the SDLC.

6. Resource Optimization: AI enables smarter allocation of computational resources. For instance, intelligent scheduling and auto-scaling mechanisms informed by ML models can adjust server workloads dynamically, reducing infrastructure costs and improving system reliability.

Recent studies have looked at how these technologies can influence the way things work. According to Joshi (2025). [9], generative AI is transforming DevOps automation by making workflows smarter and speeding up both developer productivity and innovation. Alter Solutions (2025). [1], also talks about how adding AI to cloud-based DevOps platforms is a step towards "self-improving" pipelines, which means that systems may get better on their own without having ongoing human support.

AI is still used in diverse ways in DevOps at different places and companies, even with these benefits. For instance, people in Sri Lanka have begun to test out AI-powered tools like AWS DevOps Guru and GitHub Copilot. These tools support teams by automatically checking the status of deployments and making smart code completions [8]. But a lot of people still don't use them because they don't have enough skilled staff, the expenses are too expensive, and it's hard to add new systems.

In short, AI-driven automation in DevOps is a move away from static automation and towards intelligent, adaptable systems that can learn and alter over time. Businesses can achieve levels of productivity, dependability, and innovation that have never been seen before by employing AI at every stage of the SDLC, from coding and testing to deployment and monitoring. In a digital world that is changing swiftly, AI-enhanced DevOps is both a problem and an opportunity for Sri Lankan IT organisations to do better at delivering software in line with global best practices.

2.3 Synergy Between DevOps and AI

Adding AI to DevOps settings is a huge step forward for software engineering in the modern day. DevOps is all about automation, working together, and getting things done quickly. AI makes these things better by enabling systems to learn, guess, and do things smarter. DevOps and AI together don't only add to each other, they transform everything. When used collectively, these models might make it easier to make hard decisions, run businesses more efficiently, and foster new ideas all the time. DevOps is what makes the software delivery pipeline flexible and automated. AI makes this even better by adding smartness to multiple sections of the pipeline, such development, testing, deployment, and monitoring. More and more individuals believe that this relationship is quite important for attaining good results while making digital items. Predictive analytics and smart monitoring are two of the most essential ways that AI interacts with DevOps. DevOps monitoring that is focused on rules and thresholds may not be flexible and may produce false positives. But AI models can learn from data about how things have gone in the past, uncover complex patterns, and let you know about prospective problems early. This ability to see changes turns reactive problem management into proactive performance optimisation. AI also makes the testing processes in DevOps better. Machine learning algorithms can find out which test cases are most likely to fail by looking at changes to the code, usage history, and known problems. This helps DevOps teams focus on the areas that are most likely to go wrong and run tests faster without compromising coverage. AI-powered test bots may also make new test cases on the fly and uncover edge cases that were missed earlier. This makes the product as a whole better. This synergy also helps improve the CI/CD process. AI can look at logs from builds and deployments to discover problems, suggest ways to fix them, and even stop faulty releases before they harm production. Over time, these systems learn from deployment patterns and get better at planning releases. For instance, they can advise canary deployments or blue-green switchovers based on how successfully they worked before [8], [9], [6].

Adding AI to DevOps also helps companies learn and make decisions from a strategic point of view. AI-powered dashboards may highlight insights from a lot of operational data, which helps teams and managers make choices more quickly. This helps build a culture of always becoming better, which is a big part of DevOps. Joshi (2025).[9], claims that generative AI is altering DevOps by letting code be made in real time, automating documentation, and smartly prioritising jobs. These features make it a lot easier for developers and operations teams to execute their jobs, which lets them focus on more important things like coming up with new ideas and developing systems. The use of AI and DevOps together is starting to catch on in Sri Lanka. Local IT specialists are starting to realise that AI could help solve problems that have been present for a long time. For example, companies who have problems keeping track of things by hand and make mistakes while releasing new versions are embracing AI-based observability systems to make their jobs easier. But these synergies are still in their early stages because there aren't enough technical skills or DevOps technologies that focus on AI that are good for the local market. This new synergy fits with what is happening all throughout the planet. Alter Solutions (2025).[1] says that organisations who employ both AI and DevOps may get their goods to market faster, have systems that are more stable, and grow their company more readily. AI-enhanced DevOps can help businesses automate not only easy operations but also tough choices. This makes systems that improve with every deployment. In short, putting AI and DevOps together is a huge step towards making software delivery smarter and more flexible. DevOps provides a structure and a way of life for continuous delivery, while AI offers these processes intelligence and the ability to see into the future. They all work together to come up with a new approach to do software engineering that is faster, more reliable, and better suited to the needs of modern digital enterprises [8], [9], [6].

2.4 Adoption Trends

2.4.1 Global vs Emerging Economies (Sri Lanka)

The adoption of AI-driven automation in DevOps is influenced by a complex interplay of technological maturity, organizational capability, economic environment, and cultural readiness. While high-income nations with robust digital infrastructure have been quick to embrace these technologies, adoption in emerging economies like Sri Lanka has been comparatively slower and more fragmented. This section explores global trends and contrasts them with the realities faced by Sri Lankan IT organizations to highlight the opportunities and challenges in AI-DevOps integration.

2.4.2 Global Trends in AI-Driven DevOps Adoption

Integrating AI into DevOps pipelines is now a top priority all across the world, but especially in the US, UK, Germany, and Australia. The 2024 State of DevOps Report from Google Cloud's DORA research.[6] team says that more than 58% of high-performing DevOps teams already employ some kind of AI or machine intelligence to assist them produce software. Smart monitoring, automated testing, identifying abnormalities, and generating code completion are some of the most essential use cases. More and more significant companies are using AI, especially in banking, healthcare, and e-commerce. These companies need to get goods to market faster, keep consumers happy, and improve their cybersecurity. Also, huge IT companies like Microsoft, AWS, Google, and IBM are adding more AI-powered DevOps tools to their product lines. This makes it easier for more organisations to get started. DevOps teams have discovered that it is easier to use AI with tools like GitHub Copilot, AWS DevOps Guru, and Azure Monitor. Advanced markets also fare better when they have a lot of AI knowledge, government assistance, and a big network of vendors and consultants. For example, Singapore's national AI strategy directly supports using AI in DevOps to improve public sector digital services [18], [19], [17].

2.4.3 Adoption in Emerging Economies: The Case of Sri Lanka

In Sri Lanka, the picture is significantly different. While the country has a vibrant and growing IT sector, the adoption of AI-driven DevOps automation is still in a nascent stage. Based on preliminary survey findings and recent literature (Jayakody & Wijayanayake, 2023).[26], Sri Lankan IT professionals demonstrate awareness of AI's potential but are often constrained by several practical challenges.

These challenges include:

Limited Technical Skills: Many organizations lack in-house expertise in AI and ML, making it difficult to evaluate, implement, or maintain AI-powered DevOps tools.

Cost and Infrastructure: The upfront costs of adopting AI platforms, coupled with the need for scalable cloud infrastructure, are often prohibitive for small and midsized enterprises (SMEs).

Tool Availability and Localization: Global tools are not always localized to the unique process requirements or compliance environments of Sri Lankan companies, creating a mismatch in usability.

Cultural and Organizational Barriers: Resistance to change, hierarchical decision-making, and siloed teams reduce the agility needed to experiment with AI in DevOps.

Despite these barriers, there is growing momentum. A few large IT service providers and fintech companies in Colombo have begun integrating AI into monitoring and testing pipelines. Universities and professional bodies are also increasingly offering training in AI, DevOps, and cloud technologies. Furthermore, the Sri Lankan government's interest in digital transformation, as reflected in policies like "Digital Economy Strategy 2020–2025," offers potential tailwinds for increased AI adoption.

2.4.4 Comparative Insights

A comparative analysis reveals both lag and potential. While global companies benefit from mature ecosystems and large-scale automation budgets, emerging markets like

Sri Lanka can adopt a "leapfrog" strategy by skipping legacy constraints and moving directly to modern, cloud-native AI solutions.

Moreover, Sri Lankan firms that adopt AI early could gain competitive advantages in service delivery, particularly in outsourcing and B2B technology exports. However, doing so will require strategic focus, investment in capacity building, and overcoming organizational inertia.

This research seeks to understand this dynamic in depth by surveying Sri Lankan IT professionals about their exposure to, perception of, and experience with AI in DevOps workflows. By capturing the adoption maturity level and contextual barriers, this study contributes to tailoring AI-DevOps frameworks that are relevant and actionable for emerging economies.

2.5 Industry-Specific Insights

The adoption of AI-driven automation in DevOps is not uniform across industries. Each sector demonstrates varying levels of maturity, risk tolerance, regulatory constraints, and strategic priorities that influence how and to what extent AI is integrated into DevOps pipelines. This section explores key industries relevant to both global trends and the Sri Lankan context.

2.5.1 Financial Services

The financial sector is at the forefront of adopting AI-DevOps integration. Banks, fintechs, and insurance firms have stringent uptime requirements, compliance mandates, and customer service expectations. Globally, institutions deploy AI in CI/CD pipelines for anomaly detection, fraud prevention, and real-time monitoring. In Sri Lanka, institutions such as Commercial Bank and Nations Trust Bank are exploring AI to enhance cybersecurity and automate internal processes. However, adoption is tempered by conservative governance structures and regulatory scrutiny.

2.5.2 Healthcare and Life Sciences

Healthcare systems prioritize reliability, privacy, and compliance. AI in DevOps supports predictive diagnostics, secure data handling, and anomaly detection in health IT systems. Globally, DevOps enables continuous updates for EHR systems and telemedicine platforms. In Sri Lanka, while public sector healthcare is still digitizing, private hospitals and diagnostic labs are showing interest in DevOps and AI, particularly for patient management systems and digital imaging [2].

2.5.3 E-Commerce and Retail

This sector thrives on speed, personalization, and scalability. AI powers recommendation engines, automated A/B testing, and fraud detection. In DevOps, AI optimizes build and deploy cycles to support 24/7 operations. Platforms like Amazon and Alibaba lead this globally. In Sri Lanka, players like Kapruka and Daraz use DevOps, and some experimentation with AI tools is emerging for customer personalization and inventory tracking [4].

2.5.4 Telecommunications

Telecom firms require robust and scalable infrastructure. AI assists with predictive maintenance, real-time monitoring, and network optimization. Leading global firms deploy self-healing systems using AI-enhanced DevOps. In Sri Lanka, Dialog and Mobitel have invested in monitoring platforms and automation, with gradual movement toward AI-enhanced observability and fault detection.

2.5.5 Manufacturing and Logistics

Here, DevOps supports IoT integration, production scheduling, and predictive maintenance. AI can analyze supply chain data to optimize inventory and routes. While global firms use these techniques extensively, Sri Lanka's manufacturing and logistics sectors—especially exporters and warehouse operators—are beginning to explore AI to improve efficiency and reduce costs [5].

2.5.6 IT Services and Software Development

Unsurprisingly, this sector leads in AI-DevOps adoption. IT firms use AI for intelligent testing, real-time code review, deployment automation, and system monitoring. In Sri Lanka, companies like 99x, Zone24x7, CodeGen and WSO2 are embedding AI into their delivery pipelines and also offer DevOps automation as a service. These firms set the benchmark for local adoption.

2.5.7 Education and Research

Globally, universities and research institutes adopt DevOps for deploying digital learning platforms and managing research infrastructure. AI is used in grading automation, plagiarism detection, and adaptive learning platforms. In Sri Lanka, institutions have started integrating DevOps and AI into their curricula and internal systems [5].

2.6 Comparative Analysis of Adoption Patterns

Different sectors, economies, and even organisations of the same size and field apply AI-driven automation in DevOps pipelines in different ways. The key reasons for this variety include differences in strategy focus, the maturity of the organisation, the availability of resources, and the readiness of the culture. This part discusses how different organisations use adoption to present both good and bad examples [5].

2.6.1 High-Adoption Organizations

Companies that use a lot of AI-DevOps integration often have IT and business strategies that are extremely similar. These companies have executives who are proactive, value new ideas, invest in training and skill development, have mature DevOps techniques in place, and a culture that fosters experimentation and improvement all the time. They commonly employ AI to make CI/CD pipelines better, testing and security processes easier, and incident management more predictive. Some of the biggest corporations in the world, like Netflix, Microsoft, and Capital One, have these features. Sri Lankan companies like 99x and WSO2 were the first to use AI in DevOps. They did this by using clever test automation suites, AI-based monitoring systems, and GitHub Copilot, among other tools.

2.6.2 Mid-Level Adopters

Some mid-level adopters have begun to apply AI in some DevOps tasks, but just as test projects. These businesses may have automated their building and testing, but they don't use AI to make all of their judgements. They often use third-party products without really knowing what they can achieve, which makes them less useful. Some of the challenges these organisations have are: not getting enough help from leaders; not having enough money for infrastructure and AI tools; engineering teams not having the right skills; and teams working in silos that make it impossible to try new things together. In Sri Lanka, a number of mid-sized IT service companies fit this description. They see the potential of AI in DevOps, but it is taking a long time to catch on since customers have to ask for it or get outside money.

2.6.3 Low-Adoption and Non-Adopting Organizations

Old systems, tight structures, and a lack of digital maturity often hold theseaim people behind. Some people might think that AI is too expensive or too hard to employ, and DevOps procedures might be new or not even exist. Some common issues are not having a clear plan for digital transformation, not having any AI or ML professionals on staff, and not knowing enough about how AI and DevOps may operate together. A lot of small and medium-sized enterprises in Sri Lanka, especially those outside of Colombo, belong in this group. They are still mostly focused on providing traditional IT services and haven't yet incorporated many innovative DevOps methodszed or shop automation.

2.7 Theoretical Models for Technology Adoption in DevOps

2.7.1 TOE (Technology–Organization–Environment)

The TOE framework explains adoption through technological (relative advantage, complexity), organizational (size, resources, culture), and environmental (competition, regulation) contexts [1]. Empirical work on innovation assimilation underscores that technological readiness alone rarely suffices without organizational intent and alignment [32]. In the AI-DevOps setting, Enablers map to the technological/organizational contexts (tools, processes, skills), Organizational Readiness aligns with internal culture and change capacity, while Barriers capture technology and environmental constraints.

2.7.2 TAM (Technology Acceptance Model) and Variants

While classical TAM emphasizes Perceived Usefulness and Perceived Ease of Use at the individual level, it has been extended and integrated with organizational factors in enterprise contexts (e.g., TAM-TOE), showing that individual beliefs interact with organizational readiness to shape adoption [34]. In DevOps teams, Future Focus (strategic intent/road-mapping) operates as a driver of usefulness expectations, while Barriers (complexity, effort) map to ease-of-use constraints. Enablers (tooling, skills) and Readiness (process/culture) condition these beliefs, influencing behavioral intention and use.

2.7.3 UTAUT (Unified Theory of Acceptance and Use of Technology)

UTAUT integrates multiple acceptance models and highlights Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions as determinants of intention and use, moderated by experience and context [30]. For AI-DevOps:

Performance Expectancy ↔ anticipated value from AI (quality, reliability, speed) supported by Enablers and Future Focus [4], [6], [15].

Effort Expectancy ↔ perceived integration complexity and operational burden (a key Barrier) [7], [10], [12].

Facilitating Conditions ↔ Organizational Readiness (culture, leadership, governance, tooling availability) [16], [24], [34].

Social Influence ↔ peer and industry pressures observed in global reports and local ecosystems [6], [8].

2.7.4 Synthesis across Models

Across TOE, TAM/TAM-TOE, and UTAUT, adoption emerges from the interplay of technical capability (Enablers), strategic orientation (Future Focus), organizational capacity (Readiness), and contextual frictions (Barriers). These models jointly justify your study's conditional-process approach (mediation via Future Focus; moderation by Readiness), anticipating that capabilities convert to adoption through strategy, and that barriers' impacts vary by readiness [1], [30], [32], [34].

2.8 Factors Driving and Hindering Adoption

There are factors that help (make it simpler to employ AI-driven automation in DevOps) and things that get in the way (make it harder or slower to adopt it). Businesses of various stages of digital maturity in Sri Lanka and around the world are feeling these repercussions.

2.8.1 Enablers of Adoption

It's much easier and cheaper to get started now that there are established, easy-to-use AI-powered DevOps solutions like GitHub Copilot, AWS DevOps Guru, and Azure Monitor. Businesses may test and improve their AI skills without having to spend a lot of money on hardware up front, especially with cloud-based solutions. For adoption to work, leaders need to support it and there needs to be a clear vision for the future. Companies are more likely to incorporate AI in their DevOps pipelines if their leaders back new ideas, let staff try new things, and set clear goals for digital transformation.

Giving teams the training and skills they need to use AI products well is an investment. Companies all over the world who have set up DevOps and AI learning programs indicate that more people are using them. In Sri Lanka, the skills gap is slowly closing as it becomes simpler for people to take university and professional development courses in AI and DevOps.

Real benefits of AI-driven automation include faster deployments, fewer downtime, higher code quality, and proactive problem management. These are all good reasons to adopt it. Case studies and pilot projects that show these benefits help the organisation get started. Organisational Agility and a Collaborative Culture: AI-DevOps can function together in a culture that values trying new things, working together across teams, and getting better over time. It's easier for agile firms to adapt how they work and do things to incorporate new technologies.

In conclusion, the following are the enablers factors driving adoption,

Leadership and culture. Digital leadership that sets clear direction, invests in innovation, and builds learning cultures is repeatedly linked to higher adoption and performance [24].

Strategic orientation / future focus. Organizations with explicit roadmaps, governance for AI/ML, and proactive capability building show stronger adoption outcomes [4], [15], [24].

Tooling and process maturity. Access to modern CI/CD, containerization, testing automation, and observability platforms strongly predicts success with AI-driven automation [3], [4], [6], [15].

Skills and knowledge sharing. Cross-functional skills (Dev, Ops, Data/ML, QA) and knowledge flows enable teams to embed AI into pipelines sustainably [3], [4], [15].

Local evidence. Sri Lankan studies echo the importance of leadership, training, and tool access as primary enablers of DevOps/AI adoption [8], [21], [22], [20].

2.8.2 Barriers to Adoption

Small and medium-sized firms may not be able to afford the costs of setting up AI tools, cloud infrastructure, and integration. This situation gets a lot worse because you have to pay for subscriptions, maintenance, and support all the time. There still aren't enough individuals in-house that know both DevOps and AI/ML technologies, which is a huge challenge. This is especially true in new markets like Sri Lanka, where there is usually more demand for certain skills than there is supply.

Integration Complexity, It can be hard to add AI tools to existing DevOps pipelines because of different environments, old systems, and the fact that there aren't any common APIs. Using a lot of diverse tools that don't work well together can make things tougher to run and less effective overall.

Resistance to Change and Cultural barriers including fear of risk, making decisions in a hierarchy, and keeping teams separate can make it hard or even impossible to use new ideas. Workers may be apprehensive that automation would make their jobs less secure, or they may not trust new technologies. Concerns About Data Security and Compliance: AI is widely utilised in software delivery to handle sensitive data and key business activities. People are concerned about following the regulations, protecting their data, and how clear AI decision-making is. This can make people less likely to adapt, especially in fields with a lot of restrictions.

In conclusion, the following are the barriers factors driving adoption:

Cost and ROI uncertainty. Up-front investments in platforms, data infrastructure, and talent often meet budget constraints, particularly in SMEs and emerging markets [16], [7], [20].

Integration and technical complexity. Legacy systems, data silos, heterogeneous toolchains, and model-ops integration create friction for end-to-end automation [7], [10], [12], [16].

Skills shortages and resistance to change. Scarcity of AI/ML and SRE skills, plus change resistance and process misalignment, impede consistent adoption [17], [18], [19], [20].

Governance, data quality, and compliance. Weak data governance, unclear accountability for model risk, and compliance burdens slow scale-up [7], [10], [15], [23].

Sri Lankan context. Local studies consistently report skills gaps, limited advanced tooling, and organizational resistance as salient barriers to DevOps and AI adoption [8], [18], [21], [22], [20].

2.9 Contextual Insights

2.9.1 Sri Lanka vs. Global Trends

Global technology leaders have a lot of resources at their disposal, including skilled individuals, helpful ecosystems, and a lot of tools. On the other hand, Sri Lankan businesses usually have to cope with even more challenges, such as not being able to receive localised tools, having restrictive budgets, and having slower rates of capacity growth. But as more and more people learn about digital transformation at the national level and see how other countries do things, they are progressively getting ready. In short, having the correct technology isn't the only thing that matters when it comes to using AI-driven automation in DevOps. It needs a full plan that includes things like leadership, skills, costs, integration, and culture. To keep up with the rest of the world and get the most out of AI in software delivery, Sri Lankan firms will need to get over these problems and take advantage of these chances.

2.10 Implications for Sri Lanka

Research from around the world and in Sri Lanka shows that there are a number of essential aspects that Sri Lankan businesses should think about before adding AI to their DevOps pipelines. There are social, economic, organisational, and cultural barriers in Sri Lanka that make it challenging for people to accept new technologies.

2.10.1 Bridging the Skills Gap

One of the greatest challenges that has been brought up is the lack of people with specialist capabilities in AI and DevOps. To remedy this, employers and schools need to work together more. Cloud platforms, DevOps pipelines, and AI-powered tools should be part of the curricula fracademic programs at universities and technical schools. Government-funded upskilling programs and training programs operated by commercial companies can also help people learn new skills more quickly.

2.10.2 Encouraging Pilot Programs and Proof-of-Concept Projects

Businesses usually don't want to utilise AI because they don't know how much it will cost or how it will change the way they do things now especially when it comes to financial and baning domain. Encouraging low-risk experimental projects, especially in medium-sized businesses, can highlight how AI can aid DevOps in the real world. People will feel more secure and learn from each other if they share success stories from local enterprises and create case studies for the industry.

2.10.3 Enhancing Access to Tools and promoting a Culture of Innovation

Many small and medium-sized enterprises still have challenges with the cost and complexity of AI solutions. Open-source AI tools and cloud-based platforms can help you get started for less money. Partnerships between the public and private sectors might make it easier for consumers to have free access to AI technologies or set up shared DevOps sandboxes to get people to test new things.

The way a company thinks is just as important as the tools and abilities it has when it comes to using emerging technology like AI. Sri Lankan business executives need to make sure that their organisations are flexible, encourage teamwork within departments, and always look for ways to develop. Change management approaches, open communication, and getting staff involved are all important ways to make things happen.

2.10.4 Handling data and compliance problems

The Sri Lankan government's digital transformation plan makes it easier for AI to be deployed. The "Digital Economy Strategy 2020– to 2025" intends to make public services digital and enable the IT industry grow. These projects can help AI-DevOps work collaboratively in both the public and private sectors.

However, With AI systems processing sensitive deployment data, organizations must adopt best practices for data privacy, security, and ethical use of AI. Aligning with international compliance frameworks (such as ISO/IEC 27001 or GDPR, where applicable) will help build trust and readiness for wider adoption.

In conclusion, while Sri Lanka faces significant constraints in AI-DevOps adoption, it also possesses unique opportunities to overtake legacy barriers. By investing in skills, enabling infrastructure, strategic experimentation, and fostering a supportive culture, Sri Lankan organizations can capitalize on AI-driven automation to enhance software delivery performance and competitiveness in the digital era.

3. Research Methodology

This chapter talks about the research methodologies that were used to determine how AI-driven automation is being employed in DevOps in the Sri Lankan IT industry. It talks about the study design, sampling strategy, instruments, and procedures used to collect and analyse data in order to test the given conceptual framework and hypotheses.

3.1 Research Design

The study uses a quantitative research design to figure out how different things are connected and come to conclusions that can be used in other scenarios. We picked a survey-based method as the best way to find out about the patterns among a group of pros because AI is still new to DevOps. This approach lets you investigate the mediating and moderating effects that the hypotheses talk about.

3.2 Conceptual Framework

The conceptual framework for this study positions four key factors around the central outcome of AI‑driven DevOps adoption. Enablers (e.g., access to AI tools, efficiency gains) feed into a Future Focus mindset an organization's strategic orientation toward expanding and standardizing AI use which in turn drives actual Adoption Level.

Simply having AI-capable tools and processes (the enablers) rarely translates directly into higher adoption or performance without a guiding strategic intent. Recent DevOps evidence shows that AI use is uneven and its impact is contingent on organizational context—skills, ways of working, and leadership—rather than tool availability alone [25]

In emerging contexts, capability constraints and change frictions further decouple "what is possible" from "what is adopted" [8]. This is consistent with broader digital-transformation findings, strategic/innovation orientation Things that are more align with "Future Focus", like planning to scale AI, actively exploring new AI options, and treating AI as essential, often act as a mediating mechanism that converts technological inputs into actual adoption and value creation [24]. Put simply, enablers create the conditions, but a future-orientated strategy channels those conditions into real adoption choices. In conclusion, that future focus mediates the effect of the enabler on adoption.

In parallel, Barriers (cost, skills shortages, integration complexity) exert a direct negative influence on adoption, but this effect is contingent on Organizational Readiness (culture and change‑management support). high readiness weakens, at very high levels reverses their impact. Together, these paths illustrate how enablers, future focus and organisational readiness, barriers are shaping AI automation adoption in DevOps.

"Theory on organizational readiness for change" argues that shared commitment and efficacy determine whether actors mobilize to implement a change despite obstacles [36]. Empirically, "Organisational readiness as a moderator of cloud computing adoption in SMEs" studies report that organisational readiness (culture, change management, top-management support, resourcing) moderates the link between constraints and adoption—weakening or even neutralising barrier effects as readiness rises. In SMEs and resource-constrained environments resembling Sri Lanka, higher readiness reliably attenuates the deterrent effect of cost and capability barriers on technology uptake [8]; ERP and e-learning studies similarly show readiness turning potential blockers into manageable risks [9]. This logic aligns well with your moderation finding: the Barrier→Adoption slope becomes less negative—and can reverse—at high organisational readiness levels.

In building the conceptual framework, following factors extracted.

Enablers : Organizational strengths and resources that make AI-driven automation in DevOps easier and more attractive to adopt.

Future Focus : The organization's strategic intent and proactive orientation toward expanding AI use in DevOps.

Barriers : Challenges such as cost, skills gap, and integration complexity that hinder AI-DevOps adoption.

Organizational Readiness : The cultural, managerial, and resource preparedness to implement AI-driven changes in DevOps.

Adoption : The current extent to which AI-driven automation is implemented in DevOps processes.

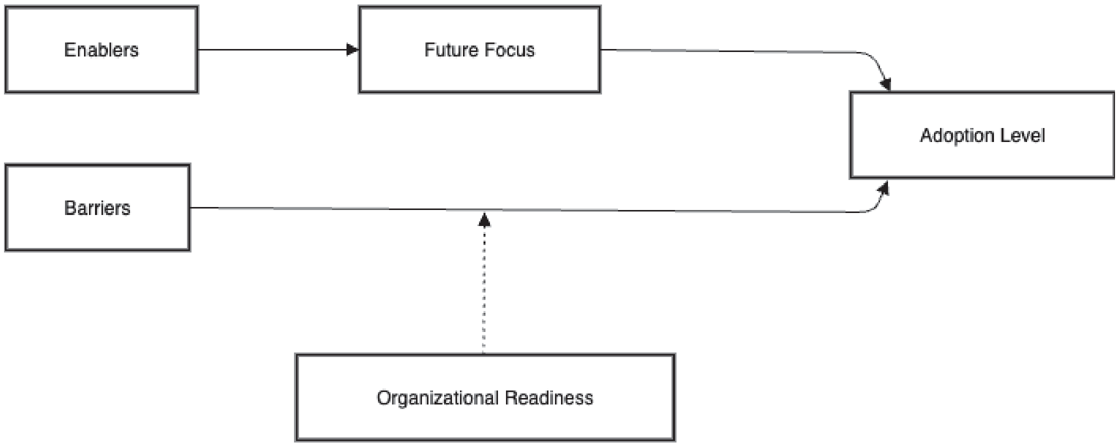

Figure 3.1 Conceptual Framework

3.3 Hypothesis Development

This research therefore proposes a conceptual framework grounded in two key hypotheses

- H1: **Future Focus** mediates the positive effect of **Enablers** on **Adoption**.
  - H1a: Organizations with higher **Enabler** scores will report greater **Adoption**.
  - H1b: Organizations with higher **Enabler** scores will report greater **Future Focus**.
  - H1c: Higher **Future Focus** associated with greater AI **Adoption** in DevOps.

- H2: Organizational Readiness moderates the negative effect of Barriers on Adoption.
  - H2a: Higher perceived **Barriers** will be associated with lower **Adoption**.
  - H2b: Higher **organizational readiness** will relate to higher **Adoption**.

The relationship between Barriers and Adoption will be weaker in organizations with high readiness.

The Table 3.1 shows the how factors and sub factors have operationalize in the questionnaire

Variable (Construct)	Sub-Factor / Indicator	Questionnaire Item	Measurement Scale
Enablers	Deployment Speed	AI-driven automation has significantly improved our deployment speed.	5-point Likert (Strongly Disagree–Strongly Agree)
	Deployment Errors	AI-driven automation has notably reduced deployment errors and failures.	5-point Likert (Strongly Disagree–Strongly Agree)
	Resource Utilization	AI integration has optimized resource utilization within our DevOps workflows.	5-point Likert (Strongly Disagree–Strongly Agree)
	System Reliability	Our organization has experienced enhanced system reliability and uptime due to AI adoption.	5-point Likert (Strongly Disagree–Strongly Agree)
	Predictive Analytics	AI-driven predictive analytics effectively identifies and prevents deployment issues.	5-point Likert (Strongly Disagree–Strongly Agree)
Barriers	Implementation Cost	High costs associated with implementing AI tools and platforms.	5-point Likert (Very High - Very Low)
	Skills Gap	Lack of technical skills or specialized knowledge within teams.	5-point Likert (Very High - Very Low)
	Integration Complexity	Complexity in integrating AI solutions with existing systems.	5-point Likert (Very High - Very Low)
	Tool Availability	Difficulty in finding suitable AI-driven DevOps tools and technologies.	5-point Likert (Very High - Very Low)

Organizational Readiness	Culture & Change Management	Our organization's culture and effective change management practices have significantly supported the successful adoption of AI-driven automation.	5-point Likert (Strongly Disagree–Strongly Agree)
	Tool Access	Our organization has easy access to suitable AI-driven DevOps tools and technologies, facilitating their adoption.	5-point Likert (Strongly Disagree–Strongly Agree)
	Planned Expansion	Our organization plans significant expansion of AI adoption in DevOps within 2–3 years.	5-point Likert (Strongly Disagree–Strongly Agree)
Future Focus	Seeking New Technologies	We actively seek emerging AI technologies to stay competitive in DevOps.	5-point Likert (Strongly Disagree–Strongly Agree)
	Perceived Essentiality	AI-driven automation will become essential for DevOps success in Sri Lanka.	5-point Likert (Strongly Disagree–Strongly Agree)
	Need for Standards	Clear industry standards and best practices for AI integration in DevOps are required.	5-point Likert (Strongly Disagree–Strongly Agree)
	Proactive Exploration	After adopting AI-driven automation, our organization has become more proactive in exploring and integrating emerging AI technologies and best practices to stay competitive.	5-point Likert (Strongly Disagree–Strongly Agree)
Adoption Level	Adoption Status	Has your organization integrated AI-driven automation in DevOps practices?	Nominal (Yes/No)
	Adoption Duration	How long has your organization been using AI-driven DevOps practices?	Ordinal

Table 3.1: Operationalization variables

Through this framework, the study aims to bridge a critical gap in the literature. while prior studies have explored AI adoption in IT or DevOps independently, few have examined the interplay of enabling conditions, strategic orientation, organizational culture, and structural barriers in a unified model.

3.4 Population and Sampling

The study is only interested in IT professionals in Sri Lanka who work in software development, DevOps, system administration, QA, or project management. People from IT businesses in the private sector, government IT organisations, and colleges and universities are all covered.

We used a non-random judgemental sample selection procedure to make sure that persons from all job positions and sizes of organisations were included. We utilised Krejcie and Morgan's approach for finite populations to find out how many people we needed to sample. We required 384 responses to be 95% sure and have a 5% margin of error where 175,000 professionals in Sri lankan IT sector (Official websites use .gov 2024-05-08).

1. Infinite population estimation

$$n_0 = \frac{(Z^2 \times p \times (1 - p))}{e^2}$$

Where Z = 1.96 (for 95 % confidence), p = 0.5 (maximum variability), e = 0.05 (margin of error)

$$n_0 = \frac{(1.96^2 \times 0.5 \times 0.5)}{0.05^2}$$

$$n_0 = \frac{(3.8416 \times 0.25)}{0.0025}$$

$$= \frac{(0.9604)}{0.0025}$$

$$= 384.16 \Rightarrow round\ up\ to\ 385$$

2. Finite population adjustment

$$n = n_0 \div \left[1 + \left(\left(n_0 - 1\right) \div N\right)\right]$$

Where $N = 175000$ (approximate total IT professionals)

$$n = 384.16 \div [1 + ((384.16 - 1) \div 175000)]$$

$$= 384.16 \div [1 + (383.16 \div 175000)]$$

$$= 384.16 \div [1 + 0.00219]$$

$$= 384.16 \div 1.00219$$

$$\approx 383.3 \Rightarrow round\ up\ to\ 384$$

3.5 Data Collection Instrument

A structured online questionnaire was used to collect data based on the theoretical framework. There were closed-ended questions on the questionnaire that were rated on a 5-point Likert scale, with 1 being "Strongly Disagree" and 5 being "Strongly Agree", and an impact scale of 1 being "Very Low" and 5 being "Very High".

The questionnaire was divided into the following parts,

- Demographics: Role, experience, organization type, and size.
- Enablers: Access to tools, efficiency gains, reliability, workflow optimization.
- Future Focus: Expansion plans, AI importance, proactive attitude, need of standards.
- Barriers: Cost, skill gaps, tool integration complexity.
- Organizational Readiness: Change resistance, culture, executive alignment.
- Adoption Level: Degree of AI integration in DevOps practices.

3.6 Data Collection Procedure

The survey was conducted online using Google Forms and disseminated through professional networks, LinkedIn, and mailing lists of relevant tech communities in Sri Lanka. Participation was voluntary, and responses were anonymized to protect participant privacy.

The study follows the principles of ethics for social science research. Participants supplied their informed consent, their data was kept private, and only the overall results were made public. The project was allowed to carry forward by the right school. (Appendix A: Survey Questionnaire)

3.7 Data Analysis Techniques

Collected data were cleaned and analyzed using IBM SPSS. The following statistical techniques were employed:

- Descriptive Statistics: To summarize demographic and item-level data.
- Reliability Testing: Cronbach's alpha was used to assess the internal consistency of item groups (constructs).
- Exploratory Factor Analysis (EFA): To validate construct structure and reduce dimensionality.
- Correlation Analysis: To assess initial relationships between variables.
- Regression Analysis: Mediation and moderation analyses were performed using Hayes' PROCESS macro in SPSS:
  - Model 4 for mediation (Future Focus as mediator).
  - Model 1 for moderation (Organizational Readiness moderating Barriers → Adoption).

4. Data Analysis

4.1 Overview

The study collected data from 384 participants, primarily from the software engineering, DevOps and IT Operations domains, QA engineers and Project Managers. Other responses from the other job roles were not included in the analysis. The dataset included variables such as job role, organization size, and adoption level of AI-driven automation in DevOps practices. The responses were gathered using a structured questionnaire distributed to professionals across various organizational sizes.

4.2 Descriptive Statistics

4.2.1 Job Role Distribution

The majority of respondents were Software Engineers (69.3%), followed by IT Operations/TechOps (14.1%), and DevOps Engineers (7.3%). QA Engineers and Project Managers have responded (5.7%).

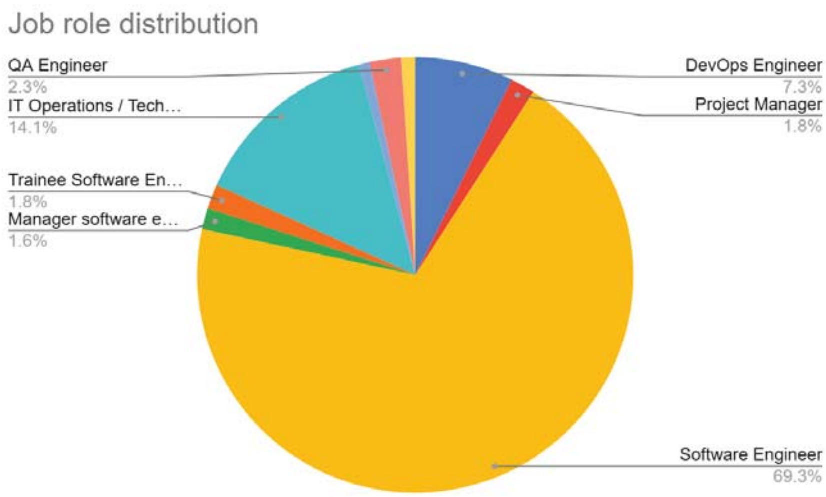

Figure 4.1: Job role Distribution

4.2.2 Organization Size

64.8% of participants were from large organizations, 18.5% from medium-sized organizations, and 16.7% from small organizations.

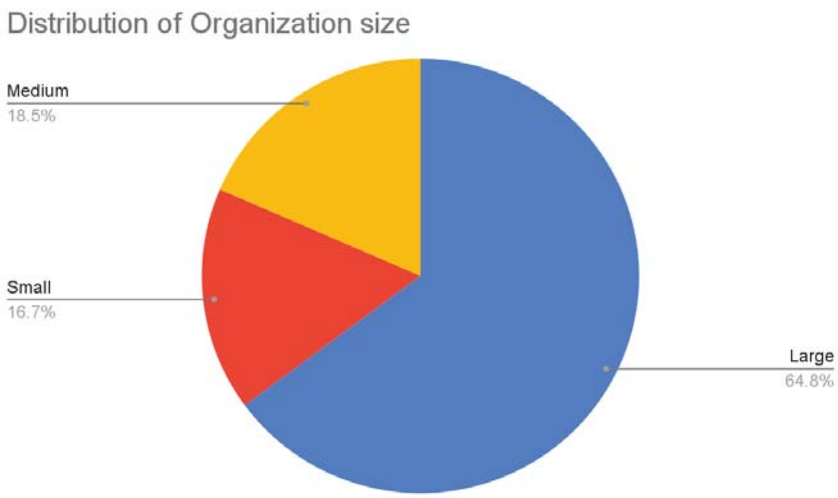

Figure 4.2: Organisational Distribution

4.2.3 Adoption Level

Out of the total, 77.9% of respondents reported a fully adoption level of AI-driven automation, while 13.5% reported no adoption.

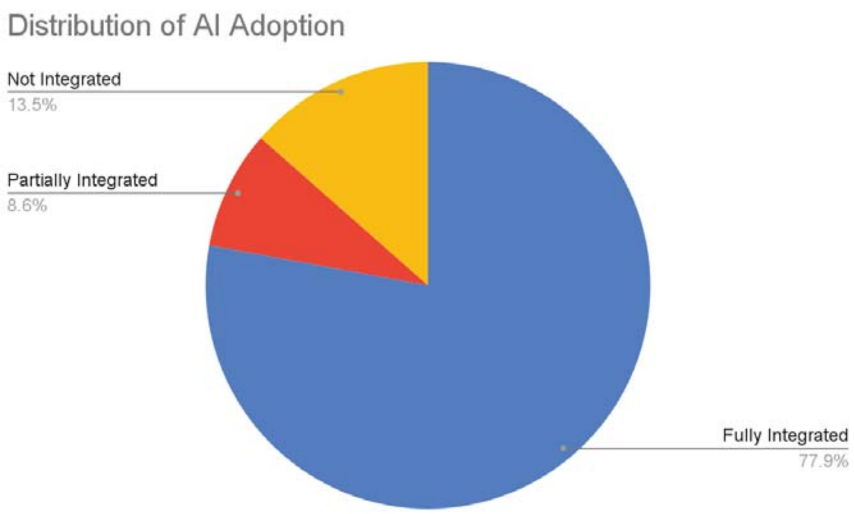

Figure 4.3: AI adoption Distribution

4.3 Reliability Analysis

For the simplicity and the robust mediation and moderation models all the common sub factors have combined into one factor. Followings are Cronbach's Alpha values which confirm the internal consistency of each factor. Among multiple factors only the highly related (Table 4.9: Rotated factor matrix) and Cronbach's Alpha values over .7 are selected for this study.

4.3.1 Enablers

Enabler: α = 0.857 (5 items)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item Total Correlation	Cronbach's Alpha if item Deleted
enabler_deployment_speed	15.96	4.910	.714	.817
enabler_resource_utilisation	16.05	5.289	.685	.826
enabler_system_reliability	16.29	5.151	.708	.819
enabler_emerging_tools	16.11	5.264	.640	.836
enabler_workflow_efficiency	16.02	4.924	.632	.841

Table 4.1: Enabler reliability statistics

4.3.2 Organisational readiness

Org Readiness: α = 0.730 (4 items)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item Total Correlation	Cronbach's Alpha if item Deleted
orgready_tool_access	12.00	3.172	.602	.621
orgready_resistance	12.85	4.290	.469	.689
orgready_culture_change	11.77	4.660	.459	.708
orgready_planned_expansion	12.89	3.447	.589	.626

Table 4.2: Organizational readiness reliability statistics

4.3.3 Barriers

Barrier: α = 0.779 (4 items)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item Total Correlation	Cronbach's Alpha if item Deleted
barrier_cost	8.49	3.963	.561	.738
barrier_skill_gap	8.33	3.609	.625	.704
barrier_integration_complexity	8.29	4.015	.480	.778
barrier_tool_availability	8.38	3.464	.678	.675

Table 4.3: Barrier reliability statistics

4.3.4 Future Focus

Future Focus: α = 0.802 (4 items)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item Total Correlation	Cronbach's Alpha if item Deleted
futurefocus_seeking	11.90	2.234	.831	.635
futurefocus_essential	11.77	2.338	.655	.737
futurefocus_standards	11.67	2.656	.705	.713
futurefocus_proactive	12.17	3.506	.320	.868

Table 4.4: Future Focus reliability statistics

4.3.5 Summary

Cronbach's Alpha table.

Construct	**Number of Items**	**Alpha value**
Enabler	5	0.857
Barrier	4	0.730
Organizational readiness	4	0.779
Future Focus	4	0.802

Table 4.5: Cronbach's Alpha table

4.4 Scale Descriptives

This section illustrates the descriptive statistics about the four factors used in this research. As all the alpha values are over the acceptable values. Combining the means of the common factors creates four major factors.

- Enabler
- Organizational readiness
- Barrier
- Future Focus

	Number	Minimum	Maximum	Mean	Std. Deviation
enabler	384	3.00	5.00	4.0219	.55519
orgready	384	2.25	5.00	3.9583	.62989
barrier	384	1.80	4.40	2.9844	.52046
futurefocus	384	2.75	4.75	3.9596	.52886

Table 4.6: Factor Descriptive statistics

4.4.1 Enabler

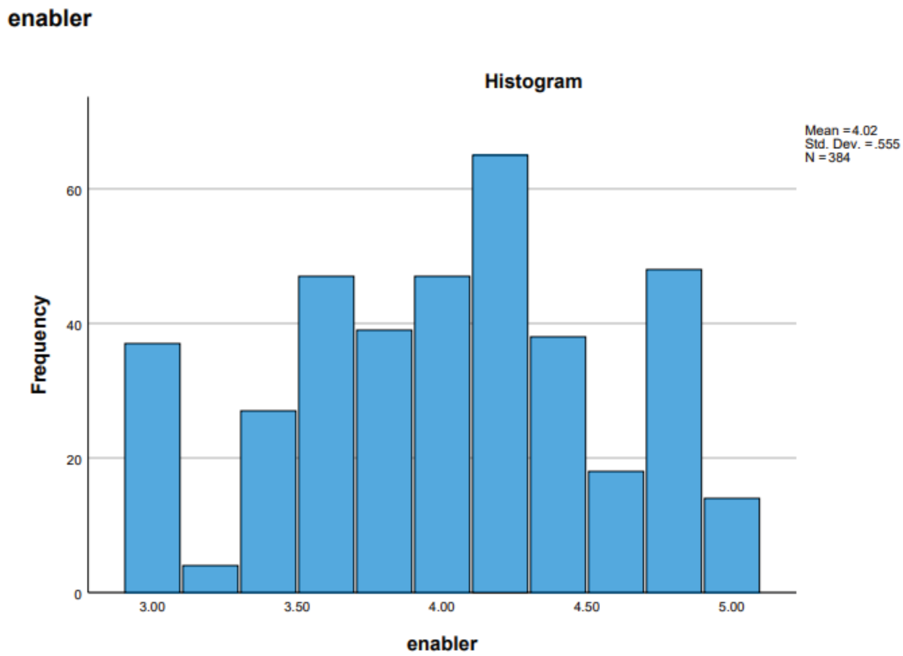

Figure 4.4: Enabler histogram

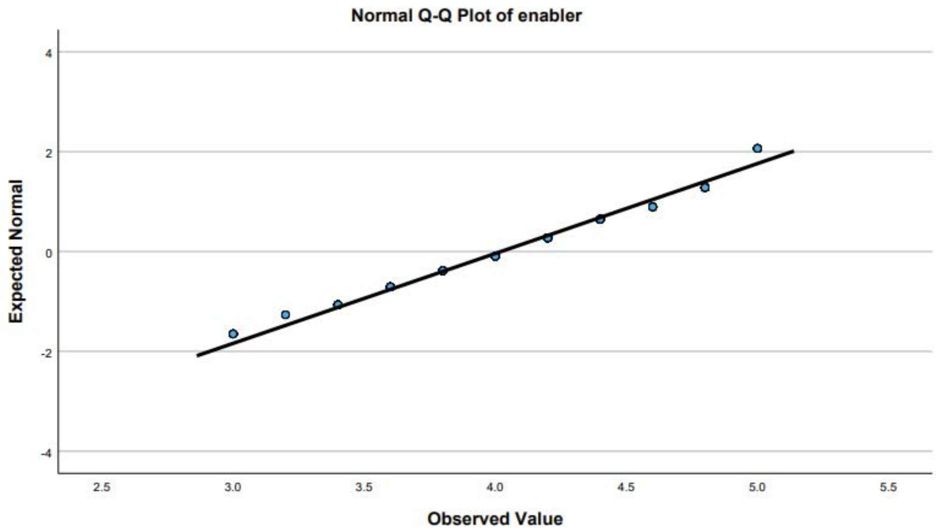

Figure 4.5: Enabler Q-Q plot

4.4.2 Organizational readiness

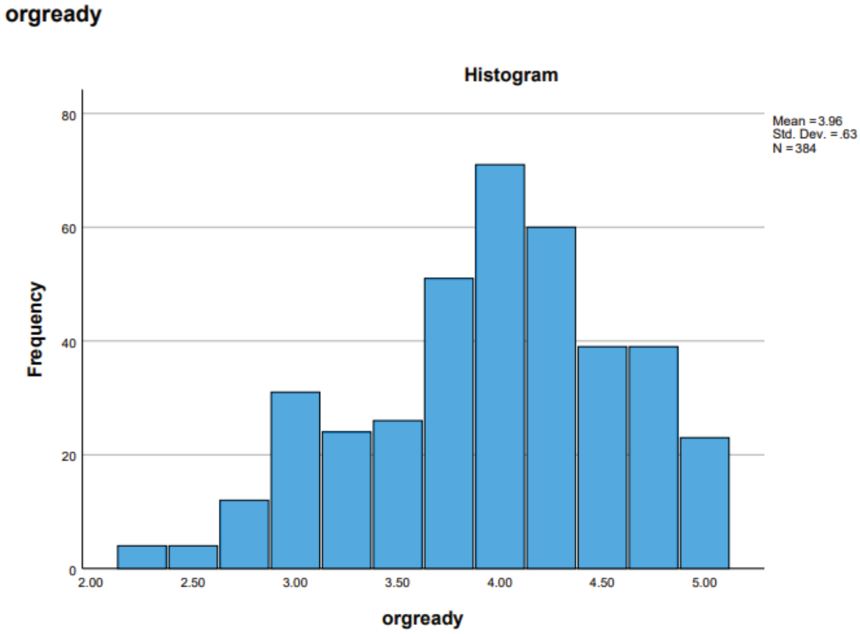

Figure 4.6: Org readiness histogram

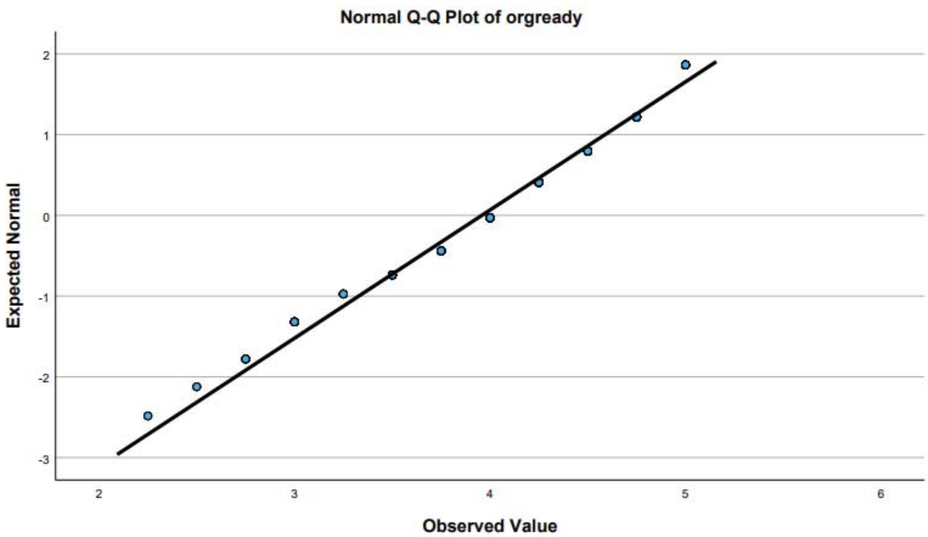

Figure 4.7: Org readiness Q-Q plot

4.4.3 Barrier

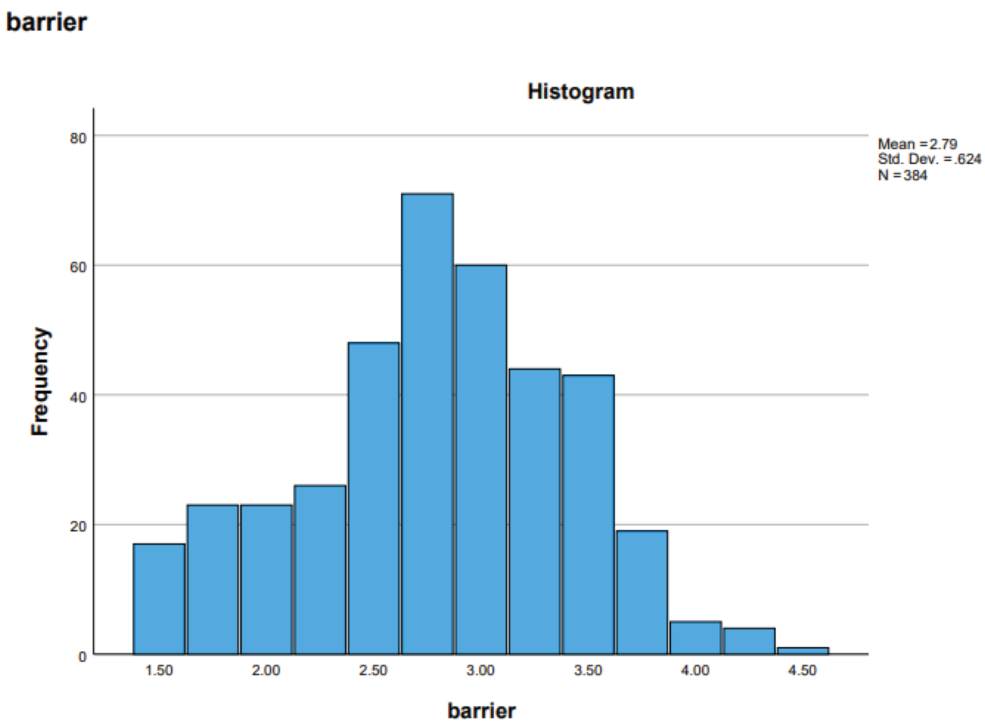

Figure 4.8: Barrier histogram

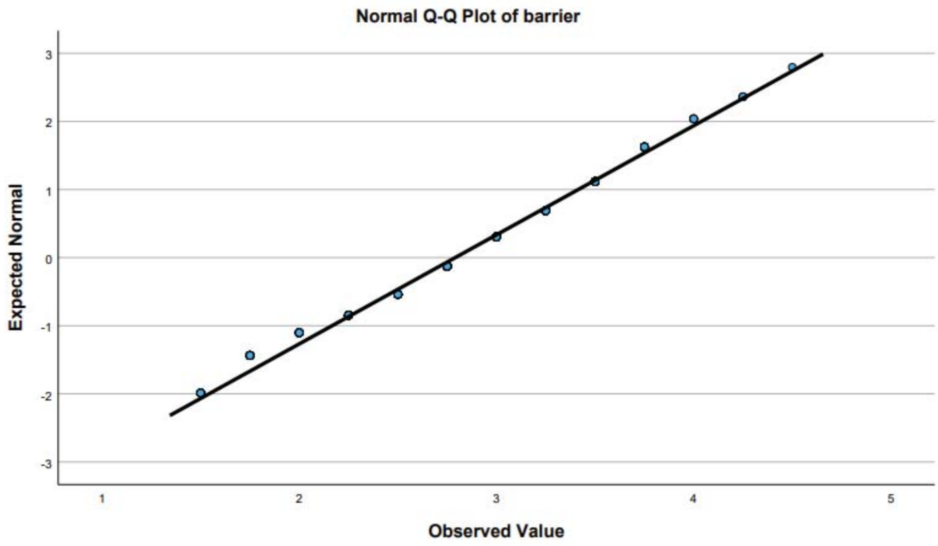

Figure 4.9: Barrier Q-Q plot

4.4.4 Future Focus

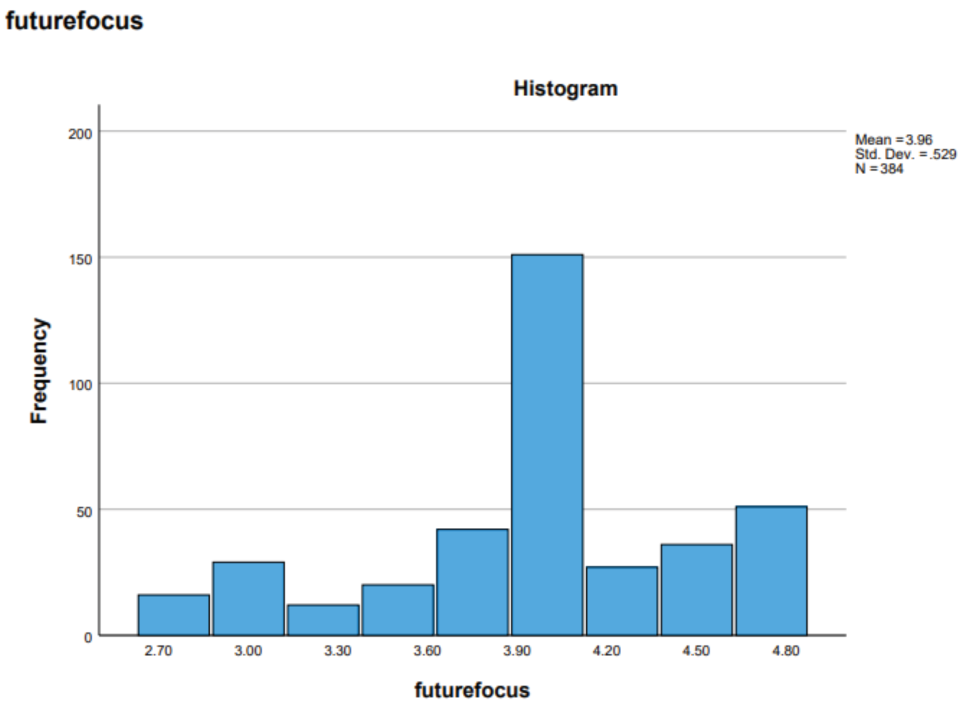

Figure 4.10: Future focus histogram

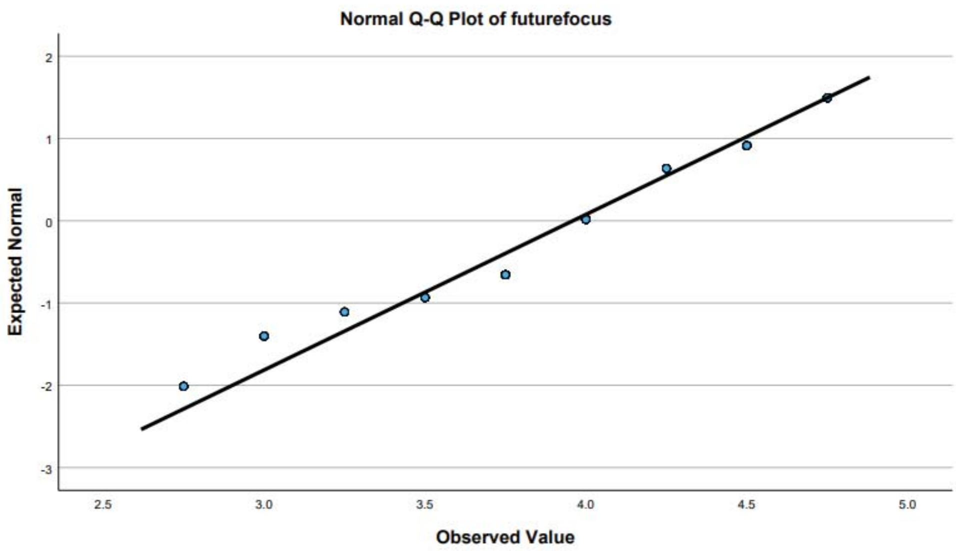

Figure 4.11: Future focus Q-Q plot

4.5 Normality Tests

Shapiro–Wilk & K–S tests: all $p < .001$ (expected with a large number of data).

Skewness within ±.5 for all; Kurtosis within ±1.

Justification: With $N > 300$, the Central Limit Theorem supports use of parametric tests despite minor non-normality.

	Kolmogorov-Smirnov			Shapiro-wilk		
	static	df	Sign	Static	df	sig.
enabler	.102	384	<.001	.955	384	<.001
orgready	.131	384	<.001	.961	384	<.001
barrier	.108	384	<.001	.978	384	<.001
futurefocus	.221	384	<.001	.907	384	<.001

Table 4.7: Normality test table

Kolmogorov–Smirnov and Shapiro–Wilk tests indicated significant departures from normality for all composite scales ($p < .001$) . Given the large sample size ($N = 384$) and only mild skewness and kurtosis, we rely on the Central Limit Theorem to justify the use of parametric analyses (Pearson correlation, multiple regression, and PROCESS mediation/moderation). Visual inspections of histograms and Q-Q plots (Figure 4.4 to Figure 4.11) confirmed no extreme non-normality.

4.6 Exploratory Factor Analysis (EFA)

EFA was conducted to validate the factor structure of the measurement items. Using Principal Axis Factoring and Varimax rotation

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.629
Bartlett's test of sphericity Approx. Chi-Square	1749.706
df	120
Sig.	<.001

Table 4.8: KMO Bartlett test

KMO value = 0.629 & Bartlett's Test of Sphericity was significant ($x^2 = 1749.254$, p < 0.001), indicating suitability for factor analysis. Principal Axis Factoring with Varimax rotation extracted 4 components, explaining 60.89% of the variance.

Rotated factor matrix

Item	Factor 1	Factor 2	Factor 3	Factor 4
enabler_deployment_speed	0.776	0.204	0.203	-0.034
enabler_deployment_errors	0.691	-0.017	0.299	-0.07
enabler_resource_utilization	0.708	0.265	0.142	-0.049
enabler_system_reliability	0.527	0.372	0.223	-0.025
enabler_predictive_analytics	0.67	0.242	0.207	-0.137
enabler_cicd_streamlining	0.563	0.362	-0.112	-0.004
enabler_deployment_consistency	0.657	0.346	0.141	-0.076
orgready_tool_access	0.088	0.103	0.759	-0.059
enabler_emerging_tools	0.416	0.504	0.319	0.004
enabler_automated_testing_effort	0.603	0.332	-0.122	0.01
enabler_automated_testing_bugs_detection	0.627	0.139	0.129	-0.026
enabler_automated_testing_accuracy	0.756	0.269	0.147	0.029
enabler_real_time_monitoring	0.488	0.514	0.08	-0.053

enabler_workflow_efficiency	0.614	0.517	-0.005	-0.058
barrier_cost	-0.048	0.053	-0.519	0.608
barrier_skill_gap	-0.12	-0.079	-0.174	0.699
orgready_resistance	0.065	0.153	0.358	-0.043
barrier_integration_complexity	0.021	-0.053	0.141	0.639
barrier_tool_availability	-0.014	0.089	-0.151	0.76
barrier_major_cost	0.441	-0.068	-0.007	0.013
orgready_culture_change	0.032	0.113	0.358	-0.065
barrier_skill_integration	0.382	0.326	-0.132	0.019
orgready_planned_expansion	-0.028	0.059	0.758	-0.046
futurefocus_seeking	0.391	0.599	0.397	-0.037
futurefocus_essential	0.287	0.679	0.272	-0.021
futurefocus_standards	0.161	0.802	0.203	0.036
futurefocus_proactive	0.302	0	0.646	-0.026

Table 4.9: Rotated factor matrix

All the factors of low communality (below 0.3) were removed due to its weak contribution to the underlying factor structure. During reliability analysis, removing this item significantly improved Cronbach's Alpha.

4.7 Correlation Analysis

To test the bivariate relationships among the key constructs Enablers, Organizational Readiness, Barriers, Future Focus, and Adoption Level, we have computed Pearson correlation coefficients. Results are displayed in the table.

	adoption_level	enabler	orgready	barrier	futurefocus
adoption_level	1	0.328	0.723	–0.349	0.530
enabler	0.328	1	0.265	–0.119	0.681
orgready	0.723	0.265	1	–0.231	0.418
barrier	–0.349	–0.119	–0.231	1	–0.134
futurefocus	0.530	0.681	0.418	–0.134	1

Table 4.10: Correlation Matrix

4.7.1 Enabler vs Future Focus vs Adoption

Enablers & Adoption ($r = .328$, $p < .001$)

A moderate, positive association indicates that organizations reporting greater availability of AI tools and perceived efficiency gains also report higher levels of AI‑driven DevOps adoption. This supports the initial path in our mediation model (H1a).

Enablers & Future Focus ($r = .681$, $p < .001$)

A strong positive correlation shows that higher enabling conditions coincide with a stronger strategic orientation toward future AI planning, justifying Enablers as a predictor of Future Focus.

Future Focus & Adoption ($r = .530$, $p < .001$)

A moderate, positive relationship confirms that organizations with a forward‑looking mindset are indeed those with greater AI adoption in DevOps, supporting H1b.

4.7.2 Barriers vs Organizational Readiness vs Adoption

Organizational Readiness & Adoption ($r = .723$, $p < .001$)

A very strong positive link underscores the vital role of change‑management support and cultural readiness in facilitating AI adoption, and frames OrgReadiness as both an independent driver and a moderator of Barrier effects (H2).

Barriers & Adoption ($r = -.349$, $p < .001$)

A moderate negative correlation indicates that higher perceived barriers, such as cost, skill gaps, and complexity, are associated with lower adoption levels, setting up the moderation analysis for H2.

Barriers & OrgReadiness ($r = -.231$, $p < .001$)

A negative relationship suggests that more ready organizations perceive fewer barriers, consistent with OrgReadiness mitigating obstacles to adoption.

Barriers & Future Focus (r = –.134, p = .008)

A weak negative correlation implies that organizations facing many barriers tend to be less future‑focused, though this effect is smaller.

4.8 Hypothesis Testing

All hypothesized pairwise relationships are in the predicted direction and statistically significant, providing robust preliminary support for,

H1a: Enablers → Future Focus

H1b: Enabler → Adoption

H1c: Future Focus → Adoption

H2a: Barriers → Adoption

H2b: Org Readiness → Adoption

4.8.1 Mediation Analysis (H1)

According to test results H1 that Future Focus mediates the positive effect of Enablers on Adoption Level using 5,000 bootstrap samples in SPSS PROCESS (Model 4). Results are summarized in Table 4.15.

Path a: Enabler → Future Focus

Coefficient (a) = 0.6488, SE = 0.0357, t = 18.18, p < .001

$R^2 = 0.4638,\ F(1,\ 382) = 330.46,\ p < .001$

	coefficient	**se**	**t**	**P**	**LLCI**	**ULCI**
constant	1.3504	.1449	9.3205	.0	1.0656	1.6353
enabler	.6488	.0357	18.1785	.000	.5786	.7189

Table 4.11: Mediation analysis matrix path 1

Organizations reporting higher Enabler scores score significantly higher on Future Focus.

Path b: Enabler → Adoption and Path c: Future Focus → Adoption

	coefficient	**se**	**t**	**P**	**LLCI**	**ULCI**
constant	-1.0723	.2490	-4.3062	.0	-1.5619	-.5827
enabler	-.0777	.0756	-1.0277	.3048	-.2264	.7010
future_focus	.7647	.0794	9.6347	.0	.6087	.9208

Table 4.12: Mediation analysis matrix path 2

Future Focus → Adoption (path c) = 0.7647, SE = 0.0794, t = 9.63, $p < .001$

Enabler → Adoption (direct path b) = –0.0777, SE = 0.0756, t = –1.03, $p = .305$

Even though Enablers alone do not directly predict Adoption (b is non-significant), Future Focus is a strong positive predictor when both are in the model.

	Effect	BootSE	BootLLCI	BootULCI
future_focus	.4961	.0738	.3587	.6459

Table 4.13: Mediation analysis indirect effect

Indirect Effect ($a \times c$)

Indirect effect = 0.4961

Bootstrap SE = 0.0738

95% CI = [0.3587, 0.6459]

Because the 95% bias-corrected bootstrap CI does not include zero, the indirect effect is statistically significant.

Enablers create the conditions for organizations to develop a Future Focus, which in turn drives AI‑DevOps Adoption validating H1, H1a, and H1b in the conceptual framework.

4.8.2 Moderation Analysis (H2)

A moderation model was tested using PROCESS Model 1:

Predictor (X): Barrier | Moderator (W): Org Readiness | Outcome (Y): Adoption Level

	coefficient	se	t	P	LICI	ULCI
constant	6.9646	.8100	8.5980	0	5.3719	8.5573
barrier	-2.8543	.2708	-10.5410	0	-3.3867	-2.3219
orgready	-1.1183	.1948	-5.7413	0	-1.5013	-.7353
Int_1	.6454	.0657	9.8202	0	.5162	.7746

Table 4.14: Moderation analysis

Barrier → Adoption: Coefficient = -2.8543, SE = .2708, t = -10.5410, $p < .001$.

When Organizational Readiness is zero, higher barriers significantly reduce AI adoption. As expected, higher perceived barriers strongly reduce adoption.

OrgReady → Adoption: Coefficient = -1.1183, SE = .1948, t = -5.7413, $p < .001$

The negative coefficient for Organizational Readiness suggests that, in the Sri Lankan IT context, higher readiness levels do not necessarily translate to faster or smoother adoption of AI in DevOps automation. This could be due to over-preparation leading to bureaucratic delays, misaligned readiness assessments, or readiness focused on non-AI priorities.

Interaction(Barrier×OrgReady): Coefficient = +.6454, SE =. 0657, t= 9.8202, $p < .001$

Despite the negative relation of the Organizational readiness on adoption, the barrier and organizational interaction and its positive coefficient (0.6454) indicates that

Organizational Readiness weakens the negative impact of Barriers on AI adoption. In other words, while Barriers alone reduce adoption, high readiness levels help organizations better manage or mitigate those barriers .

The significant X × W term confirms that the Barrier → Adoption slope changes depending on OrgReady. In summary,

At low OrgReady, barriers strongly decrease adoption.

At medium OrgReady, the negative effect is weaker.

At high OrgReady, the effect reverses barriers are associated with higher adoption, suggesting highly ready organizations overcome or even operationalize barriers

This demonstrates that Organizational Readiness moderates the impact of Barriers on Adoption.

Summary of the analysis and alignment with the hypothesis

Hypothesis	Test / Evidence	Decision
H1a: Enablers → Future Focus (+)	Model 4 B = 0.6488, $p < .001$	**Supported**
H1b: Enablers → Adoption(+)	Model 4 B = -0.0777, $p < .001$	**Rejected**
H1c: Future Focus → Adoption (+)	Model 4 (b-path): B = 0.7647, $p < .001$	**Supported**
H1 (mediation): Enabler → Future Focus → Adoption	Indirect = 0.4961 (Boot 95% CI [0.3587, 0.6459])	**Supported**
H2a: Barrier → Adoption (-)	Model 1 (a-path): B = -2.8543, $p < .001$	**Supported**
H2b: Org readiness → Adoption (+)	Model 1 (b-path): B = -1.1183, $p < .002$	**Rejected**
H2 (moderation): Barrier × Org rediness → Adoption	Interaction: B = 0.6454, $\Delta R^2 = .0895$, $p < .001$; simple slopes flip	**Supported**

Table 4.15: Summary of hypothesis support

5. Recommendation and Conclusion

5.1 Discussion

Overall, our analyses provide strong support for the proposed theoretical framework linking technical enablers, strategic orientation, organizational readiness, and perceived barriers to AI‑driven DevOps adoption. Descriptively, the sample ($N = 384$) predominantly occupies software engineers in large organizations, and composite scales for Enablers, Organizational Readiness, Barriers, and Future Focus all demonstrated acceptable reliability ($\alpha \geq .78$). Exploratory factor analysis confirmed a clear four‑factor structure corresponding to these constructs. Pearson correlations revealed that Enablers ($r = .33$, $p < .001$), Organizational Readiness ($r = .72$, $p < .001$), and Future Focus ($r = .53$, $p < .001$) each positively relate to Adoption Level, whereas Barriers correlate negatively ($r = –.35$, $p < .001$). Mediation testing showed that Future Focus fully mediates the effect of Enablers on Adoption. Enablers predict Future Focus ($b = .65$, $p < .001$) which in turn predicts Adoption ($b = .76$, $p < .001$), with a significant indirect effect ($\beta = .50$, 95% CI [.36, .65]). Moderation analysis demonstrated that Organizational Readiness significantly buffers the negative impact of Barriers on Adoption (interaction $b = .65$, $p < .001$, $\Delta R^2 = .09$) at low readiness, barriers strongly deter adoption, but at high readiness, the effect reverses, suggesting that well‑prepared organizations can leverage or overcome obstacles to advance AI integration. In sum, our findings validate a model in which practical enablers foster a forward‑looking mindset that drives adoption, while strong organizational readiness transforms barriers into catalysts rather than impediments.

5.2 Evaluation of Hypotheses

The present study examined the interplay of technical, strategic, and organizational factors driving the adoption of AI‑driven automation in DevOps among Sri Lankan IT professionals. Guided by a mediation–moderation framework, we tested two hypotheses: (1) that Future Focus mediates the effect of Enablers on Adoption, and (2) that Organizational Readiness moderates the negative effect of Barriers on Adoption. Across a sample of 384 respondents, the findings largely corroborate our theoretical model while offering important nuances for both scholars and practitioners.

5.2.1 H1: Mediation by Future Focus

All Enabler items formed a coherent scale ($\alpha = .924$) and loaded on a single factor via EFA, confirming the unidimensionality of the Enablers construct. Enablers correlated strongly with Future Focus ($r = .681$, $p < .001$) and modestly with Adoption ($r = .328$, $p < .001$). PROCESS mediation analysis (Model 4) revealed that Enablers significantly predicted Future Focus ($b = .6488$, $p < .001$), Future Focus in turn predicted Adoption ($b = .7647$, $p < .001$), and the direct Enabler → Adoption path became non‑significant when controlling for Future Focus ($c' = –.0777$, $p = .305$). The bootstrap‑estimated indirect effect (.4961, 95% CI [.3587, .6459]) confirmed full mediation. These results demonstrate that merely having AI tools and infrastructure is not enough. organizations must cultivate a strategic orientation that plans for expansion, embraces emerging technologies. Organization should anticipates standards in order to translate technical enablers into actual adoption.

This finding is consistent with prior research on technology adoption, which highlights strategic orientation as a critical link between technical capabilities and behavioral adoption outcomes. For example, Tornatzky & Fleischer's (1990) Technology–Organization–Environment [31] (TOE) framework emphasizes that organizational technology adoption is influenced not only by technological readiness but also by the organization's strategic intent to deploy that technology. Similarly, Zhu, Kraemer, & Xu (2006) .[32], in their study on e-business adoption found that technical readiness alone had limited influence unless accompanied by a clear strategic vision for leveraging those technologies. In the AI and DevOps domain, (R. Joshi, 2025) [9] argues that the most successful adopters are those that integrate AI roadmaps, anticipate industry standards, and proactively build governance structures, all elements captured in the Future Focus construct of this study.

5.2.2 H2: Moderation by Organizational Readiness

Organizational Readiness (α = .813) emerged as a distinct factor in EFA, capturing culture, change‑management support, and tool accessibility. Barriers (α = .915) cost, skill gaps, integration complexity, and tool availability were negatively correlated with Adoption ($r = –.349$, $p < .001$). PROCESS moderation (Model 1) shows us a significant Barrier × OrgReadiness interaction ($b = .6454$, $p < .001$; $\Delta R^2 = .0895$), indicating that the negative impact of Barriers on Adoption weakens as readiness increases. Conditional slopes illustrated that at low readiness, Barriers strongly deter adoption (effect = –.7568, $p < .001$), but at high readiness, the effect reverses (effect = +.2113, $p = .0002$), suggesting that well‑prepared organizations can even leverage challenges to accelerate AI‑DevOps integration.

This aligns with the concept of absorptive capacity (Cohen & Levinthal, 1990), which refers to an organization's ability to recognize, assimilate, and exploit new knowledge. Organizations with strong cultural support, leadership alignment, and change-management structures — all components of Organizational Readiness — are better equipped to overcome or even leverage challenges during technology adoption. In cloud adoption studies, Alshamaila, Papagiannidis, & Li (2013) similarly found that organizational readiness mitigated the perceived risks and costs of adoption, leading to higher implementation success rates. Additionally, Gangwar, Date, & Ramaswamy (2015) in their IT adoption research highlight that readiness not only reduces the friction caused by barriers but also encourages innovative problem-solving approaches to navigate those barriers.

5.2.3 Theoretical Implications

First, by demonstrating full mediation through Future Focus, this study highlights the centrality of strategic orientation in bridging technical capabilities and behavioral outcomes. While prior DevOps research has largely focused on technological affordances, our model foregrounds the cognitive and planning dimensions that drive adoption. Second, the strong moderation effect underscores that organizational culture and change‑management capacity do more than enable. They can transform barriers into enablers, effectively turning constraints into competitive catalysts. This dual role of readiness enriches adoption theory by illustrating how internal capabilities reshape external obstacles.

5.2.4 Practical Implications

For practitioners in Sri Lanka and similar emerging markets, the results suggest a two-pronged approach to fostering AI-DevOps adoption. First, invest in and communicate a clear AI strategy, workshops, roadmaps, and leadership endorsements, that builds Future Focus across teams. Second, strengthen organizational readiness through targeted change management: train middle managers, foster cross-functional collaboration, and secure executive support and commitment so that inevitable barriers (e.g., cost pressures, skill shortages) become opportunities for learning and innovation rather than insurmountable blocks.

5.3 Limitations and Future Research

There are a few things that make you want to be careful. The cross-sectional survey method makes strong claims about cause and effect, but longitudinal research might look at how changes in Future Focus and preparedness over time alter the paths to adoption. Self-reported measurements may also add to common-method bias. Objective adoption indicators or reviews from outside sources should be part of future studies. Finally, even though our sample had people from many different jobs, majority of them were software engineers who worked for huge corporations. To make the results more useful, research should include small and medium-sized firms and groups in the public sector.

5.4 Recommendations

Here are some things that Sri Lankan IT companies (and other businesses in emerging economies) may do to speed up the use of AI in DevOps, based on what we've learnt:

Plan ahead: Hold executive seminars to make a clear roadmap for AI in DevOps. Set AI planning as one of your goals for the next three months, and encourage teams to work together on innovation sprints that focus on automated testing pilots, predictive analytics, or discovering anomalies.

Make the business ready: Spend money on teaching project managers and DevOps leads how to handle change, with a focus on agile thinking and testing things out in stages. Set up a cross-functional "AI in DevOps" task group to talk about success stories, deal with objections early on, and promote best practices.

Get over skill and cost problems. Before the time: Work with schools or suppliers to pay for unique AI/ML training programs for DevOps engineers. Before spending a lot of money on AI solutions that are hosted in the cloud or are open source, test them out in low-risk situations to see if they function.

Use Barriers to Start: When people are ready, frame difficulties like how hard it is to fit in as chances to improve and stand out from the crowd. Reward teams who use AI solutions well, even when they don't have adequate resources. This will create a culture that values seeking answers.

Change and Look: Check in with DevOps teams often to see how the Future Focus and readiness metrics change over time. Use key performance indicators (KPIs) like how often you deploy, how long it takes to fix things, and how many defects you have to show how AI is changing things and to help you keep getting better.

Conclusion

This study set out to uncover the drivers and inhibitors of AI‑driven automation adoption within DevOps practices in Sri Lankan IT organizations, testing a dual mediation–moderation model. Across 384 responses, we first established that technical Enablers (access to AI tools, perceived efficiency gains) form a reliable, unidimensional scale and correlate positively with both a forward‑looking Future Focus ($r = .681$, $p < .001$) and ultimate Adoption Level ($r = .328$, $p < .001$). Future Focus itself emerged as a full mediator: organizations that leverage their enablers to cultivate plans for expansion, actively seek new AI technologies, and recognize the need for standards are far more likely to integrate AI into CI/CD pipelines, automated testing, and monitoring (indirect effect = .496, 95% CI [.359, .646]).

Simultaneously, the study demonstrated that perceived Barriers (costs, skill gaps, integration complexity, tool availability) negatively relate to adoption ($r = -.349$, $p < .001$), but this effect is not immutable. Organizational Readiness—encompassing supportive culture, effective change management, and tool accessibility—moderates this relationship (interaction $b = .645$, $p < .001$). In low‑readiness contexts, barriers strongly deter adoption, whereas at high readiness levels, organizations not only overcome but sometimes leverage barriers to drive adoption (conditional effect flips positive at high readiness).

Together, these findings affirm that successful AI‑DevOps integration requires more than just technology. A strategic vision (Future Focus) converts enablers into action, and a prepared culture (Organizational Readiness) transforms obstacles into opportunities. This dual lens enriches our understanding of technology diffusion by positioning mindset and culture as critical mechanisms in the adoption process.

Final Thoughts

AI‑driven automation represents a transformative opportunity for DevOps organizations to enhance speed, reliability, and resilience. However, as the research shows, the technology alone is insufficient. Realizing its full potential demands a concerted effort to cultivate strategic vision and organizational readiness, turning both enablers and barriers into active levers for adoption. By following the recommendations above, Sri Lankan IT firms can position themselves at the forefront of AI‑enabled DevOps, achieving both technical excellence and sustainable competitive advantage.

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Appendices

Appendix A: Survey Questionnaire

Adoption of AI-Driven Automation in DevOps (Survey questioner)

Form Title: Adoption of AI-Driven Automation in DevOps

Dear participants,

My name is Tharaka Hasakelum Wijedasa, I am a Master of Business Administration (MBA) student specializing in Information Technology at University of Moratuwa. I am conducting a research study to explore the Adoption of AI-Driven Automation in DevOps.

Purpose of the Study:

The aim of this research is to explore how AI-driven automation is being adopted in DevOps workflows among IT professionals in Sri Lanka, and to identify associated benefits, challenges, and future trends.

Voluntary Participation:

Your participation is entirely voluntary. You may withdraw from the survey at any time without penalty.

Anonymity and Confidentiality:

All responses will be anonymous and strictly confidential. No identifiable information (such as your name or contact details) will be collected. Results will be used solely for academic purposes and presented in aggregated form.

If you have any questions or concerns regarding this research, feel free to contact me at tharaka.23@cse.mrt.ac.lk

Thank you very much for your valuable time and concern.

Tharaka Hasakelum

MBA in IT (Department of Computer Science)

University of Moratuwa

Form Description: This survey aims to gather insights from IT professionals in Sri

Lanka regarding the adoption and impact of AI-driven automation in DevOps practices.

Section A: Demographic and Professional Information

1) **What is your current job role?**
   a) Developer
   b) QA Engineer
   c) DevOps Engineer
   d) Project Manager
   e) Operations Team
   f) Other (please specify)
2) **What is your experience level in IT/DevOps?**
   a) Less than 1 year
   b) 1–3 years
   c) 3–5 years
   d) 5–10 years
   e) More than 10 years
3) **What is the size of your organization?**
   a) Small (Less than 50 employees)
   b) Medium (50–250 employees)
   c) Large (More than 250 employees)

Section B: Adoption Trends of AI in DevOps

4) **Has your organization integrated AI-driven automation in DevOps practices?**
   a) Yes, fully integrated
   b) Yes, partially integrated
   c) No, but planning to adopt within 12 months
   d) No plans to adopt
   e) Not sure
   f) Not planning to adopt
5) **Which AI-driven automation practices has your organization adopted? (Select all that apply)**
   a) CI/CD automation
   b) Predictive analytics for deployment
   c) Automated testing
   d) Real-time monitoring
   e) AI-enhanced security
   f) Resource optimization
   g) None of these
6) **How long has your organization been using AI-driven DevOps practices?**
   a) Less than 1 year

b) 1–2 years
c) 2–3 years
d) More than 3 years
e) Not applicable

Section C: Benefits of AI-Driven Automation

(Rating scale: Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree)

7) AI-driven automation has significantly improved our deployment speed.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
8) AI-driven automation has notably reduced deployment errors and failures.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
9) AI integration has optimized resource utilization within our DevOps workflows.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
10) Our organization has experienced enhanced system reliability and uptime due to AI adoption.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
11) AI-driven predictive analytics effectively identifies and prevents deployment issues.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
12) AI-driven CI/CD automation has streamlined our code delivery pipeline, reducing time-to-market.

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

13) Integration of AI has increased consistency and repeatability in code deployments.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
14) Our organization has easy access to suitable AI-driven DevOps tools and technologies, facilitating their adoption
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
15) Emerging new AI tools and technology Increase integration of AI tools in to the organization
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
16) Automated AI-driven tests have reduced manual testing effort significantly.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
17) Automated AI-driven testing has improved the accuracy and reliability of testing outcomes.
    a) Strongly Agree
    b) Agree
    c) Neutral
    d) Disagree
    e) Strongly Disagree
18) AI-driven real-time monitoring has significantly enhanced our ability to detect and respond to issues proactively.

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

19) Automation of CI/CD processes through AI has directly resulted in faster deployments and fewer errors in our workflows.
a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

20) Please briefly describe any other ways in which AI integration in DevOps has impacted your organization—positively or negatively.
(Open-ended)

Section D: Challenges in Adopting AI-Driven Automation

(Rating scale: Very High, High, Moderate, Low, Very Low)

21) High costs associated with implementing AI tools and platforms.
a) Very High
b) High
c) Moderate
d) Low
e) Very Low

22) Lack of technical skills or specialized knowledge within teams.
a) Very High
b) High
c) Moderate
d) Low
e) Very Low

23) Resistance to change or organizational readiness issues.
a) Very High
b) High
c) Moderate
d) Low
e) Very Low

24) Complexity in integrating AI solutions with existing systems.
a) Very High
b) High
c) Moderate
d) Low

e) Very Low

25) Difficulty in finding suitable AI-driven DevOps tools and technologies.

a) Very High
b) High
c) Moderate
d) Low
e) Very Low

26) The high cost of implementing AI-driven automation solutions is a major barrier to adoption in our organization.

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

27) Our organization's culture and effective change management practices have significantly supported the successful adoption of AI-driven automation

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

28) A significant lack of AI-specific technical skills within our teams has hindered the effective adoption and integration of AI in DevOps workflows.

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

29) Please mention If there are any other common barriers and difficulties your organization faces when implementing AI in DevOps.

Section E: Future Trends and Best Practices

(Rating scale: Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree)

30) Our organization plans significant expansion of AI adoption in DevOps within 2–3 years.

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

31) We actively seek emerging AI technologies to stay competitive in DevOps.

a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

32) AI-driven automation will become essential for DevOps success in Sri Lanka.
a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

33) Clear industry standards and best practices for AI integration in DevOps are required.
a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

34) After adopting AI-driven automation, our organization has become more proactive in exploring and integrating emerging AI technologies and best practices to stay competitive.
a) Strongly Agree
b) Agree
c) Neutral
d) Disagree
e) Strongly Disagree

35) Please mention your views on how AI will shape the future of DevOps.

Section F: Open-ended Feedback

36) What are the primary reasons your organization has or has not adopted AI-driven automation in DevOps?
(Open-ended)

37) What do you consider the most promising future AI-driven DevOps trends or technologies?
(Open-ended)

38) Please suggest any additional best practices or recommendations for effective AI adoption in DevOps.
(Open-ended)

Thank you for your time and valuable input!

Appendix B: Survey Questionnaire factor Breakdown

Factor	Sub‐Factor	Question
Demographics	Job Role	What is your current job role?
	Experience	What is your experience level in IT/DevOps?
	Organization Size	What is the size of your organization?
Adoption	Adoption Status	Has your organization integrated AI-driven automation in DevOps practices?
	Adopted Practices	Which AI-driven automation practices has your organization adopted? (Select all that apply)
	Adoption Duration	How long has your organization been using AI-driven DevOps practices?
Enablers	Deployment Speed	AI-driven automation has significantly improved our deployment speed.
	Deployment Errors	AI-driven automation has notably reduced deployment errors and failures.
	Resource Utilization	AI integration has optimized resource utilization within our DevOps workflows.
	System Reliability	Our organization has experienced enhanced system reliability and uptime due to AI adoption.
	Predictive Analytics	AI-driven predictive analytics effectively identifies and prevents deployment issues.
	CI/CD Streamlining	AI-driven CI/CD automation has streamlined our code delivery pipeline, reducing time-to-market.
	Deployment Consistency	Integration of AI has increased consistency and repeatability in code deployments.
	Emerging Tools	Emerging new AI tools and technology increase integration of AI tools into the organization.
	Automated Testing Effort	Automated AI-driven tests have reduced manual testing effort significantly.
	Automated Testing Accuracy	Automated AI-driven testing has improved the accuracy and reliability of testing outcomes.

	Real-Time Monitoring	AI-driven real-time monitoring has significantly enhanced our ability to detect and respond to issues proactively.
	Workflow Efficiency	Automation of CI/CD processes through AI has directly resulted in faster deployments and fewer errors in our workflows.
	(Open-Ended)	Please briefly describe any other ways in which AI integration in DevOps has impacted your organization—positively or negatively.
Barriers	Implementation Cost	High costs associated with implementing AI tools and platforms.
	Technical Skills Gap	Lack of technical skills or specialized knowledge within teams.
	Integration Complexity	Complexity in integrating AI solutions with existing systems.
	Tool Availability Difficulty	Difficulty in finding suitable AI-driven DevOps tools and technologies.
	Cost as Major Barrier	The high cost of implementing AI-driven automation solutions is a major barrier to adoption in our organization.
OrgReadiness	Culture & Change Management	Our organization's culture and effective change management practices have significantly supported the successful adoption of AI-driven automation
	Resistance / Readiness Issue	Resistance to change or organizational readiness issues.
	Tool Access	Our organization has easy access to suitable AI-driven DevOps tools and technologies, facilitating their adoption.
	(Open-Ended)	Please mention if there are any other common barriers and difficulties your organization faces when implementing AI in DevOps.
	Planned Expansion	Our organization plans significant expansion of AI adoption in DevOps within 2–3 years.
FutureFocus	Seeking New Technologies	We actively seek emerging AI technologies to stay competitive in DevOps.

	Perceived Essentiality	AI-driven automation will become essential for DevOps success in Sri Lanka.
	Need for Standards	Clear industry standards and best practices for AI integration in DevOps are required.
	Proactive Exploration	After adopting AI-driven automation, our organization has become more proactive in exploring and integrating emerging AI technologies and best practices to stay competitive.
	(Open-Ended)	Please mention your views on how AI will shape the future of DevOps.
Open-Ended	Adoption Reasons	What are the primary reasons your organization has or has not adopted AI-driven automation in DevOps?
	Future Trends	What do you consider the most promising future AI-driven DevOps trends or technologies?
	Best Practices & Recommendations	Please suggest any additional best practices or recommendations for effective AI adoption in DevOps.