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The role of Artificial Intelligence in modern workflow automation platforms: A systematic literature review on Apify and Make

[1]Sajid Saleem, [2]Olusegun Shefiu Ganiyu, [3]Chukwuemeka Odi Agwu, [4]Vaithiyalingam Subramanian Manjula, [5]Akiteng Immaculate,[6]Asiimwe John Patrick

[1,2,6]Department of Information Technology, School of Mathematics and Computing, Kampala International University, [1]sajid.saleem@kiu.ac.ug, saleem.sajid.14955@gmail.com
[2]ganiyu.shefiu@kiu.ac.ug, [6]jp.asiimwe@kiu.ac.ug
[3,5]Department of Computer Science, School of Mathematics and Computing, Kampala International University, [3]chukwuemeka.odi@kiu.ac.ug, [5]immaculate.akiteng@kiu.ac.ug
[4]Professor, Department of Computer Science, School of Mathematics and Computing, Kampala International University, manjuisne2015@gmail.com manjula.subramanian@kiu.ac.ug
Orcid: https://orcid.org/0000-0003-0308-3289

Abstract

The workflow automation solutions, such as Apify and Make, now offer greater functionalities because to the rapid growth of AI. AI brings dynamic decision making, adaptive learning, and intelligent optimization to organizational workflows, whereas automation systems used to concentrate on rule-based automation. I examine the effects of AI on workflow automation systems in my review of the literature, paying particular attention to cloud automation, enterprise API integrations, workflow model design, and domain-specific automation use cases. The integration of current research to determine AI automation trends, obstacles, and opportunities. With a particular emphasis on Apify and Make.com to show how AI and workflow orchestration are convergent. In order to highlight the revolutionary consequences of AI the review divides the results into the subjective grouping after conducting a methodological examination of the academic articles, technical documents and business white papers. The data shows that AI enhances the scalability and adaptability of workflow automation that creates challenges concerning to system design and integration as well as ethical concerns. The use of advanced applications in the industries like automated network management and healthcare demonstrate the adaptability of the AI-based systems. The study indicates that although AI enhances the workflow automation but still there are significant challenges remain to exist in standardization, clarity and adaptability across different domains. This highlights specific problems that require more attention and as well as the need for future automation related innovations.

Keywords: Artificial Intelligence, Workflow Automation, Integromat, Apify, Make, Workflow Orchestration

1. Introduction

AI technologies have changed these platforms by including new features, including predictive analytics natural language processing, and automated decision-making (Forni et al., 2023). Apify and Make platforms demonstrate how current solutions utilize AI to increase the scalability, adaptability, and intelligence of workflow orchestration. As a result of advancements in machine learning and cloud computing, workflow automation occurs. This is the reason for conducting this study. Historically, automated systems had to rely on rigid structures and required manual override for even the smallest modifications (Lippi & Da Rin, 2019). Self-optimizing and instantly adapting to changing demands machine learning-based workflows provide solutions to the previous limitations of artificial intelligence (Kammer et al., 2000). Consider a complex puzzle. AI-driven project management tools can dynamically modify the puzzle pieces to make sure the project continues smoothly, moving tasks from one group to another based upon who has the resources or proactively addressing delays prior to their escalation (Panagos & Rabinovich, 1997). Examples include managing projects more efficiently in the IT industry or managing patient care in the healthcare industry through intelligent automation that reduces the time to make decisions (Dai & Abràmoff, 2023). In addition to the items already mentioned, there are several other factors to consider. First, the lack of standardization in integrating AI into workflow management makes for fragmented and inefficient system deployments (Wiggins et al., 2021). Secondly, While AI may enhance automation capabilities the "black box" nature of the majority of these automated systems are creating problems of reliability and accountability especially in highly regulated markets (Schemmer et al., 2022). Alum et al. (2026) address the "black box" challenge by exploring strategies to build clinical trust through AI interpretability. Thirdly, those areas that have little need for high levels of specialization, such as, Regulatory Compliance within the Healthcare Industry or Delay Thresholds in Network Automation, are still being ignored in the context of AI-based Workflow Research (Chen et al., 2024). It therefore seems reasonable to undertake a Systematic Review to collate current research knowledge and potentially identify avenues for Future Research. This research was prompted by the capability of AI to alter the underlying paradigm of workflow automation and the lack of a comprehensive examination of its use in Platforms such as Apify and Make.

2. Methodology

2.1. Review Protocol

Followed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the researchers employed an exhaustive search across multiple databases, using only databases that have established themselves as leading sources for engineering and computer science literature. The authors decided to use IEEE Xplore as a primary source because it is the most extensive peer-reviewed publication archive for automation and AI research. Because of its focus on software systems and workflows, the writers also included the ACM Digital Library. The researchers used Web of Science, Scopus, ScienceDirect, SpringerLink and Google scholar to ensuThee a multidisciplinary approach to accessing high-quality technical papers and emerging li terature. The search strategy used multiple keywords and phrases related to AI and workflow automations platforms to target tools like Apify and Make.com without excluding reviews, surveys or meta-analysis. To eliminate publications that did not contain research, several measures were implemented by the authors to limit the scope of the publication types. To obtain the best possible results, several refinements were performed to the terms to ensure that only relevant publications would be considered and to limit the number of irrelevant publications that could be retrieved. Finally, AI in Other Domains includes other categories of applications than those described above.

2.2. Inclusion and Exclusion Criteria

To identify studies to include in this study, the following criteria were applied: (1) Each study directly examined AI combined with workflow automation platforms. (2) Each study included technical or empirical information concerning Apify, Make or other systems of the same nature. (3) All studies were written in English. (4) All studies were peer-reviewed. Studies lacking empirical data, studies evaluating theoretical models that have not been implemented, and duplicated studies were removed from consideration based upon the exclusion criteria. There are no temporal restrictions regarding the studies to capture the evolution of AI in automation over time, but the authors have omitted non-peer-reviewed preprints and opinion articles to maintain academic integrity.

2.3 Study Selection Process

Authors utilized the four steps of the PRISMA selection process to determine which studies would be considered for inclusion: Step 1 Identification - Identify all possible studies to consider. Step 2 Evaluation for Suitability - Evaluate the relevance of each identified study. Step 3 Evaluation for Eligibility - Determine if each study meets the inclusion/exclusion criteria. Step 4 Final Inclusion - Include all studies meeting the previous criteria in the literature synthesis. The authors began their investigation with 889 studies found in their database searches. Duplicate studies were removed from consideration, resulting in a total of 288 studies. Following title/abstract screening, a further 180 studies were removed from consideration as irrelevant. A full-text review was then performed on the remaining 75 studies. Based on the results of the full-text review, the authors determined that 56 studies were eliminated from consideration due to insufficient technical details and/or an unrelated focus, leaving 19 studies for synthesis.

Figure 1, a PRISMA flow chart illustrates this loss of studies and highlights the rigorous standards applied throughout the selection process.

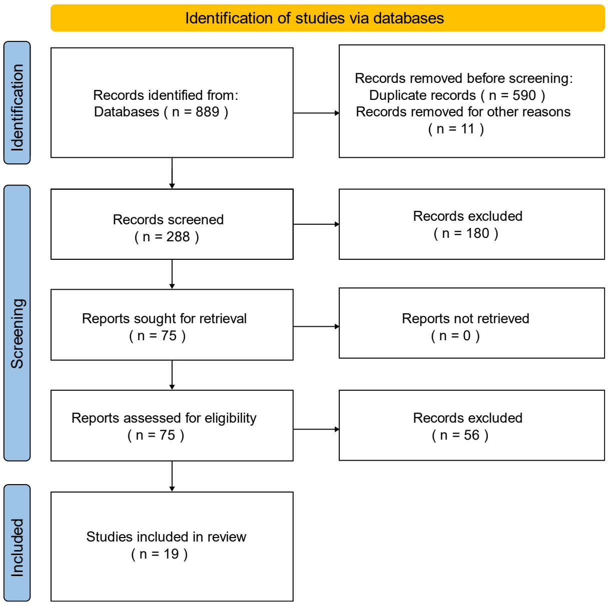

Figure 1. PRISMA flowchart of study selection process

Potential biases include publication bias toward positive results and the predominance of technical studies over real-world case analyses. To address this limitation, industry reports containing grey literature were examined when peer-reviewed data were insufficient. However, the emphasis on Apify and Make could restrict broader applicability to alternative platforms, a limitation imposed by the review's specific focus.

3. Results

3.1. Research Trends

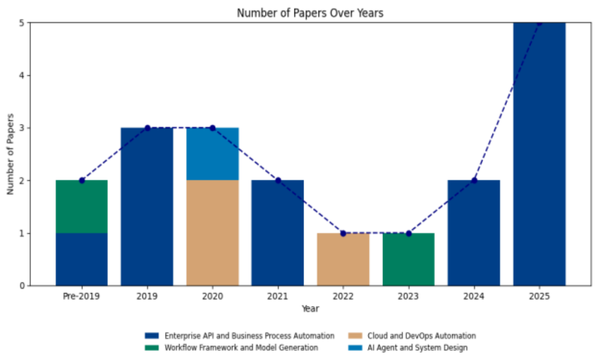

Figure 2. Research trends in the domain of AI in modern workflow automation platforms

There is evidence of an increasing amount of scholarly interest regarding AI-based workflow automation in comparison to the last six years based upon the amount of studies that have been completed in this area. In comparison to 2018 when only two studies were completed, there were three studies completed in 2019. In 2020, three further investigations were finished. Lastly, two studies were finished in 2021 and 2022. however, two studies were finished in 2023 compared to 2021 and 2022, and five studies were finished in 2024 and two in 2025 compared to 2023. The general trend of the number of researches conducted in this field indicates that awareness of AI's potential to change workflows has grown over time, most likely as a result of advancements in cloud computing and machine learning technology. Many of the studies reviewed cantered around Enterprise API and Business Process Automation. Enterprise API and Business Process Automation are the most researched topics in this data set and they represent the largest portion of studies that were reviewed. The large number of studies regarding Enterprise API and Business Process Automation is reflective of the increasing adoption of AI in allowing different parts of organizations to integrate and collaborate with one another in order to create workflows in organizations.

There are fewer studies regarding Workflow Framework and Model Generation compared to those of Enterprise API and Business Process Automation, but both remain areas of ongoing research interest. As previously stated, the research in Cloud and DevOps Automation reached its peak in 2020 and the research regarding AI Agent and System Design remains an emerging area of study. The limited number of studies in the dataset regarding Network Automation, Medical and Laboratory Automation, and other areas of study reflect either underutilized opportunities for conducting research in the identified areas or emerging areas of study. It appears that researchers initially focused on establishing basic knowledge in the organizationally integrating and designing of workflows and then transitioned to more specialized areas of study, specifically cloud automation. The significant growth in the number of studies completed in 2025 regarding the application of AI in scalable and intelligent automation solutions, indicates that the industry may be creating a demand for solutions in this area. The trend also reflects broader technological trends towards the use of AI to improve workflows. The disparity in the number of studies completed in various subtopics, indicate a need for a greater balance of research in areas of study that are currently receiving less attention.

3.2. AI-Driven Enterprise API and Business Process Automation

The use of AI in conjunction with Company APIs and Business Process Automation represents a major innovation in Work Flow Management Systems. Studies in this area have demonstrated how AI enables traditional automation to provide adaptive decision-making and intelligent process orchestration. The taxonomy presented in Table 1 categorizes these studiess based on application domain, technology approach, and primary skill, and demonstrates both the variety and specialization of current research in this area.

Table 1. Taxonomy of AI applications in enterprise API and business process automation

Application Domain	**Technology Focus**	**Key Capabilities**	**Sources**
Workflow Management	Robotic Process	AI-enhanced workflow monitoring	(Singasani, 2021)

	Automation (RPA)	and data-driven decision making	
	Process Mining	Integration challenges with AI automation technologies	(Rasaq, 2025)
Financial Services	Business Process Management (BPM)	Regulatory compliance automation	(Singasani, 2021)
	Customer Relationship Management (CRM)	Platform-based process automation	(Singasani, 2021)

The authors point out that, research regarding robotic process automation (RPA) have shown how artificial intelligence can transform static workflows into dynamic systems that can adjust in real time. As shown in Singasani's (2021) study, Pega and RPA are integrated through machine learning to assess workflow structure and enhance job and resource distribution. Furthermore, Singasani (2021) notes that one of the main drawbacks of conventional RPA systems was their incapacity to carry out sequential predetermined tasks regardless of context or content; in contrast, an AI-enhanced iteration offers both proactive insights to anticipate changes and predictive insight to anticipate bottleneck issues and boost throughput. Using AI-driven automation in conjunction with process mining technology presents a number of unique issues, according to Rasaq (2025). AI enabled Business Process Management Systems have successfully provided value in automating regulatory compliance requirements in the financial services industry. According to Singasani (2021), the automated execution of compliance checks using Natural Language Processing and Anomaly Detection in Pegas BPM platform resulted in significant decreases in the number of manual reviews of financial reporting. Furthermore, the CRM function available in such platforms shows how artificial intelligence can personalize customer interactions, while keeping compliant records. The capabilities of AI enabled automation provide a vital role to highly regulated industries; however, as mentioned in the studies, there are many significant barriers to explainable and auditable AI decision making. In total, these various technologies show the emergence of a new paradigm for Enterprise Automation Platforms as intelligent intermediaries between separate systems. Modern systems are not just connected by means of multiple APIs; instead, artificial intelligence allows them to interpret the data, establish Service Level Agreements (SLAs), and dynamically update workflows to reflect shifting business goals. The transition from Rule-Based Automation to Cognitive Automation represents a fundamental shift in how businesses envision and manage their business processes; however, it also creates new challenges for governing and verifying system performance.

3.3. AI-Enhanced Workflow Frameworks and Model Generation

New types of Model Generation and Workflow Optimization have been made possible by AI-enhanced Workflow Frameworks. With an emphasis on the work of Joshi and Chavan (2023) and others, this subsection explores the role of AI in real-time pattern detection and adaptive process design to transform traditional workflow systems (Podhorszki et al., 2007).

Table 2. Taxonomy of AI Applications in Workflow Framework and Model Generation

Application Domain	AI Model Characteristics	Sources
Media Analysis	Uses deep learning models for temporal/spatial pattern detection in media	(Joshi & Chavan, 2023)
Scientific Computing	Implements atomic AI operations with success/failure states for data processing	(Podhorszki et al., 2007)

Joshi & Chavan (2023) depicts the structural nature of Deep Learning Models utilised in Workflow Systems for Temporal and Spatial Analysis of Media Data. CNNs are used in a deep fake detection method to find frame-level abnormalities in a video, while RNNs are used to find temporal irregularities in the video sequence. This allows the system to determine the possibility of truthfulness of the media with proper documentation of reasoning. The modular pipeline separates feature extraction, temporal analysis, and final classification into distinct and interconnected phases, and the AI modules are integrated into the workflow framework. These frameworks illustrate how artificial intelligence can enhance specific workflows, yet maintain the system's integrity and user-friendliness. Podhorszki et al. (2007) outline an approach in scientific computing whereby AI processes are viewed as singular-step actions, and therefore, have well-defined success/failure states. Each AI module in the plasma fusion simulation workflow is treated as a task that either succeeds or invokes a predetermined set of corrective action(s). As a result of this design, it is believed to be essential for high-performance computing environments where it is important to manage partial failures so as not to bring other parts of the workflow to a halt. Unlike traditional workflow systems that utilize coarse retry policies, the atomic-operation model enables fine-grain escalation, recovery and redistribution of resources. Furthermore, the authors describe regions where such systems can be utilized with existing scientific workflow tools and, therefore, outline a strategy for incrementally embedding AI features into legacy scientific workflows. Collectively, these studies represent all aspects of integrating AI in workflows - from focused deep learning models to generalized atomic operation frameworks. The media analysis case demonstrates the AI-layered vertical application targeting unique pattern recognition, whereas in scientific computing, there exists a more universal enhancement of workflow robustness and error recovery. Both emphasize the need to maintain workflow architecture and clarity in the presence of AI complexity, indicating that the successful inclusion of AI relies on finding a thoughtful balance between the power of automation and the ease of managing the system.

3.4. AI-Powered Cloud and DevOps Automation

This Section, using an analysis of evidence from studies (Patchamatla & Owolabi, 2020; Vangala, 2022; Ganesan, 2020) aims to reveal the ways in which AI drives these areas through automated Quality Assurance, Smart Monitoring, and Dynamic Resource Allocation.

Table 3. Taxonomy of AI Applications in Cloud and DevOps Automation.

Automation Focus	Platform/Technology	AI Integration Approach	Sources
AI Workflow Optimization	OpenStack with Kubernetes	Dynamic resource allocation for AI workflows	(Patchamatla & Owolabi, 2020)
MLOps Automation	Cloud-native platforms	Automated model deployment, monitoring, retraining	(Vangala, 2022)
DevOps Automation	SonarQube	AI/ML integration for code quality analysis	(Ganesan, 2020)

Patchamatla & Owolabi (2020), propose using Serverless Computing and Kubernetes Orchestration in OpenStack Environments to enhance the efficiency of AI Workflows; to manage the variation in processing AI Pipelines, the framework dynamically allocates resources to match current workloads. This method of dynamically allocating resources can significantly reduce costs for computationally intensive processes such as model training and inference. Additionally, the integration of Kubernetes provides the capability to perform fine grained container management; enabling the framework to individually optimize each element of the workflow. These capabilities, provide examples of how AI has the potential to be enhanced through intelligent Scheduling and Resource Management Algorithms, as well as having the capability to be benefited by automated cloud operations. The platforms of MLOps represent a primary interface between DevOps and AI through automation, according to Vangala, 2022. In the paper, the author presents a model for continuous deployment and assessment of machine learning models on cloud native environments. The proposed model is a closed-loop model of continuous feedback, in which performance metrics are continuously assessed to determine whether a model needs to be re-trained. Anomaly detection algorithms are used to detect instances of concept drift and data quality issues, and to automatically trigger corrective actions based upon predefined escalation paths. The presentation of an automated closed-loop model demonstrates the role of AI in supporting DevOps, and therefore demonstrates the feasibility of creating self-sustaining systems that continuously evolve and adapt to changes in their data environment. Research has shown that AI can be applied to improve the quality assessments of source code (Ganesan, 2020). In addition to utilizing machine learning to enhance SonarQube's static analysis features with an understanding of previous historical defect patterns, the AI aspect identifies previously undetectable, complex code defects and categorizes them according to the potential severity of their impact on system stability.

Further, it is stated by the authors that the "Smart" priority function will allow for a reduction in the number of alerts that developers will receive, allowing the developers to focus their time on the most impactful issues. Additionally, the authors have stressed the importance of integrating AI-assisted quality assessments into development pipelines, so that the technical debt continues to decrease throughout the entire software development lifecycle. The studies indicate a common theme of a paradigm shift; where AI is no longer just a consumer of cloud services, but instead, is proactively involved in performing many of the tasks that were traditionally considered part of DevOps. The OpenStack use case represents the "smarts" at the Infrastructure layer, while the MLOps use case illustrates the "flexibility" at the Application layer. The improved version of SonarQube is representative of the manner in which AI is being incorporated into current development tools, resulting in a comprehensive ecosystem of "smart", automated applications. The various use cases demonstrate the AI role in both Cloud and DevOps, and demonstrate how the AI is represented as customized changes to a specific phase in the workflow and/or business objective(s). However, the research demonstrates a common challenge in achieving transparency and oversight within these AI-based systems, specifically when a series of automated processes traverse multiple organizational boundaries and/or legal jurisdictions.

3.5. AI in Network Automation

AI in Network Automation is a growing body of research that addresses problems associated with Configuration Management, System Observation and Security. In this section we discuss how AI impacts traditional Network Operations through Intelligent Optimization, Predictive Analytics and Autonomous Threat Response.

Table 4. Taxonomy of AI Applications in Network Automation.

Application Area	Automation Approach	Key Technologies	Sources
Network Configuration Management	AI-driven configuration optimization	Machine learning, NLP	(He et al., 2025; Pardesi, 2024)
	Automated policy enforcement	Rule-based systems	(Chintam, 2025)
Network Monitoring & Troubleshooting	Predictive failure detection	Deep learning, time-series analysis	(Onteddu, 2025; Abubakar & Volikatla, 2021)
	Automated root cause analysis	Knowledge graphs, causal inference	(Khayatbashi et al., 2025)
Network Security Automation	Threat detection & response	Anomaly detection, reinforcement learning	(Ilieva & Nikolov, 2019; Zhan et al., 2024)
	Automated vulnerability patching	AI-assisted code generation	(Ray et al., 2019)

Optimization of Network Configuration Utilizing AI is a significant advancement in network management, demonstrated in (He et al., 2025) and (Pardesi, 2024). These studies utilize Machine Learning Algorithms to analyze network topology and data flow patterns, resulting in optimized configurations that balance performance, security and resource utilization.

AI enabled natural language processing enables interpretation of High-Level Policy Requirements, and conversion to Device-Specific Directives without violating Organizational Standards. AI reduces errors due to manual setup and dynamically adapts to changing network environments, however, limitations exist regarding ensuring interpretability of configurations created by artificial intelligence. Onteddu (2025) and Abubakar & Volikatla (2021), utilizing deep-learning Architectures, analyze temporal data from networking equipment, and identify subtle anomalies prior to them becoming actual faults. Thus, these systems have greater accuracy than traditional threshold alarms, examining multivariate correlations and temporal dependencies across network metrics. Lastly, Methodologically, the Work of Khayatbashi et al. (2025), extends Root-Cause Analysis, utilizing Knowledge Graph-Driven Reasoners, where Causal Relationships among Network Entities allow identification of Faults within Large Scale and Multi Layered Infrastructures. Therefore, the aforementioned Techniques can be used collectively to form a Closed Loop Anomaly Detection and Remediation Suggestion System, thereby reducing Average Repair Time. Artificially-Intelligent Technologies have been a notable feature in transforming aspects of Security Automation, as illustrated in (Ilieva & Nikolov, 2019) and (Zhan et al., 2024). Anomaly Detection Models are Trained on Network Traffic Logs to Discover Attacks that Bypass Signature-Based Systems, and Reinforcement Learning is Utilized to Train Adaptive Responses to Attacker Behaviors. A New Approach to Remediation for Vulnerabilities Utilizing AI-Assisted Code Generation was presented in Ray et al. (2019), Where AI Assists in Automatic Patches for Security Flaws in Network Device Configurations. AI has been used for large-scale security intelligence, but human involvement is still needed in mission-critical environments. AI's role in network operations has expanded from assistive to autonomous decision-making, improving system verification and operational processes. However, challenges arise due to diverse network environments and critical network services. A balance between automation and human oversight is needed for service reliability and network security.

3.6. AI Agent and System Design for Workflow Automation

A major area of research in intelligent process orchestration is the development of AI agents and systems to perform workflow automation. This section discusses how artificial intelligence modifies traditional automation architecture through autonomous decision-making, adaptive learning, and lifecycle management for all processes in a single end-to-end manner.

Table 5. Taxonomy of AI applications in agent and system design

AI Lifecycle Stage	Automation Approach	Sources
End-to-end AI Lifecycle	Humans-in-the-loop automation	(Wang, Ram, Weidele, Liu, Muller, et al., 2020)
	Data cleaning to model deployment	(Wang, Ram, Weidele, Liu, Muller, et al., 2020)

Data cleaning to model deployment (Wang,Ram, Weidele, Liu, Muller, et al., 2020)

Wang, Ram, Weidele, Liu, Muller et al. (2020) developed a full end-to-end framework for completely automating all aspects of AI, via human-AI collaboration, in the form of Auto AI. As an example of how the complete workflow for machine learning can be fully automated from start to finish starting with data processing and ending with the deployment of the trained models' intelligent agents manage repetitive optimization tasks. This has addressed a major challenge of the AI community gaps between data preparation, development of algorithms and deployment. The proposed system utilizes meta-learning to provide an algorithm that fits the characteristics of each dataset and then creates the pipeline configuration and evaluates it automatically. At each validation gate, there is adequate human input provided, to create an environment where standard decisions are automated and significant ones remain with humans. This model is continuously deployed and thus is critical to the “humans in the loop” process to ensure continued model performance. The Auto-AI framework provides monitoring agents to continuously monitor model performance and activate retraining pipelines if performance degrades. It can autonomously retrain AI systems, aiding in production AI systems management. Explanation Generation Tools help generate explanations for automated decisions, enabling human confirmation. AI can enhance the complexity of AI methods, with Data Cleaning Agents and Hyper-Parameter Tuning Components efficiently searching parameters. Consistent operational automation and traceability are challenges, but AI-based system designs can enable widespread automation.

3.7. AI in Medical and Laboratory Automation

The incorporation of AI into the medical and laboratory environments has produced remarkable improvements in diagnostic precision, productiveness in the workplace, and speed of research in medical and laboratory workflows. This section describes how AI fundamentally alters clinical and lab processes via intelligent sample analysis, predictive scheduling, and experiment automation.

Table 6. Taxonomy of AI Applications in Medical and Laboratory Automation

Application Area	Automation Focus	AI/ML Techniques	Sources
Clinical Diagnostics	Sample Processing & Analysis	Deep Learning for Image Analysis	(He et al., 2025; Pardesi, 2024)
		NLP for Report Generation	(Onteddu, 2025)
	Workflow Optimization	Predictive Scheduling	(Chintam, 2025)
Laboratory Research	High-Throughput Screening	Computer Vision for Plate Reading	(Abubakar & Volikatla, 2021)
	Experimental Automation	Robotic Process Automation	(Khayatbashi et al., 2025)

Many studies have described several significant impacts that can be made within clinical diagnosis: He et al. (2025), and Pardesi (2024). Both studies employed Convolutional Neural Networks in their analyses of medical imaging data for the purpose of diagnosing tumors and identifying specific cell types. These two studies provide evidence for the feasibility of employing these deep learning models in conjunction with Laboratory Information Systems in order to provide real-time analysis of radiology and pathology samples. Thus, the time-consuming manual processing of samples is eliminated and, simultaneously, stringent quality criteria continue to be maintained. Nonetheless, there exist a number of challenges associated with ensuring consistency in the performance of models with respect to both patient populations and imaging equipment. Onteddu (2025) provides evidence through his research supporting the concept of Natural Language Processing transforming clinical reporting processes. His research presents an AI-enabled system that creates structured diagnostic reports from unstructured clinical notes and laboratory findings. A clinical note or a laboratory finding is fed into the NLP pipeline where clinically relevant entities are extracted, relationships between findings are inferred, and the resultant output is formatted according to medical documentation standards. Consequently, the amount of clerical burden placed upon healthcare professionals is reduced while, at the same time, the quality of the data used in downstream analytical processes is improved. However, it has been noted that for general-purpose systems of NLP, it is necessary to train domain-specific language models using medical corpora since they do not understand complex clinical terminology and context. Predictive scheduling algorithms optimize laboratory workflows by predicting the volume of testing and required resources. Chintam (2025) proposed a machine-learning model to predict daily workloads based on historical test patterns, seasonal trends, and other external influences including trends related to public health. This system continuously reschedules staff and machine usage in large diagnostic laboratories to minimize bottlenecks. Accordingly, the proactive scheduling model discussed in this study serves as a prime illustration of how artificial intelligence can also be used to improve operational effectiveness in health care delivery environments that have limited resources. In addition to the requirements outlined above, the authors emphasized that the scheduling system should produce explicit recommendations to facilitate human review and decision-making for the allocation of scarce resources. Further, artificial intelligence enables computer vision to automate the analysis of high-throughput screening assay data from the laboratory. Specifically, Abubakar & Volikatla (2021) developed an architecture for plate-reading using deep-learning, wherein image-recognition algorithms interpret cellular response to numerous test conditions, at scale, compared to the ability of humans to interpret such data. Furthermore, these methods are significantly more accurate than a human's capability to identify subtle phenotypic differences that would have been missed. Therefore, they can provide rapid evaluation of compound efficacy and potential dosage variations to expedite the drug discovery process. Moreover, the incorporation of the robotic liquid handling systems provides the base-element of the closed-loop experimental workflow; in which, AI directs future experiments based on real-time analysis of intermediate data resulting from previous experiments. Consequently, the study conducted by Khayatbashi et al. (2025) presents the opportunity for Robotic Process Automation (RPA) to automate and streamline many of the time consuming and monotonous tasks typically associated with laboratory activities. Specifically, the study demonstrates the use of RPA in the form of AI driven robots to perform sample preparation, reagent dispensation and instrument calibration during molecular biology processes. Moreover, RPA systems are capable of eliminating errors and increasing throughput as they function continually throughout the day and require no human intervention. Nevertheless, the authors of the study indicate that there are unique considerations for robotics process automation for laboratories related to both biological variability and instrument compatibility; therefore, whenever feasible, robotics process automation for laboratories should utilize robust mechanical systems combined with flexible AI-based control software. Manjula and Karamagi (2018) demonstrate precision in robotic automation using pick-and-place systems that require minimal human assistance. Thus, the combination of these two technologies represents the first step toward completely autonomous laboratory environments, wherein AI will manage every aspect of experimental workflows from design to the interpretation of results.

3.8. Comparative Analysis: Apify vs. Make

Apify and Make are workflow automation tools, but they have distinct orientations. Apify is a cloud-based environment for web scraping and executing browser-based tasks, while Make is a general-purpose automation tool for creating complex workflows using over 300 platforms. Both tools utilize artificial intelligence for automation, but their differences highlight the range of automation from domain-specific to enterprise-wide integration.

Table 7. Comparative analysis of Apify vs. Make

Feature	Apify	Make (Integromat)
Core Orientation	Specialized in web scraping and data extraction with limited scheduling/automation	Comprehensive workflow orchestration across 1,500+ SaaS and enterprise apps
AI Integration	NLP and LLM-driven actors for adaptive scraping, entity recognition, and error recovery	Pre-built AI modules (OpenAI, Vision, speech-to-text) embedded in flow scenarios
Strengths	Robust scraping at scale, structured data delivery (JSON, CSV, APIs)	Broad automation, enterprise connectors, drag-and-drop builder
Limitations	Narrow domain: cannot orchestrate enterprise processes	Not suitable for heavy web scraping or unstructured web data
Use Cases	Market research, compliance monitoring, e-commerce price tracking	CRM/ERP integration, finance, HR workflows, cloud DevOps
Role in AI Automation	Demonstrates AI-enhanced data acquisition, feeding downstream automation	Demonstrates AI-enhanced process orchestration, coordinating system-level workflows

As shown in Table 8, Apify excels where automation requires sophisticated data extraction and adaptive agents/actors, whereas Make is stronger for orchestrating complex enterprise workflows across multiple SaaS platforms. This comparative lens highlights how AI's role in workflow automation is shaped not only by domain but also by the architecture and strategic orientation of the platform.

4. Discussion

The examined literature reveals that AI is altering workflow automation by moving it beyond rigid, rule-based processes toward more flexible and intelligent systems. Traditional workflow tools were generally meant to follow predefined stages, but AI now allows these systems to adjust to changing conditions, discover patterns, and facilitate more flexible decision-making. This transition is obvious in platforms such as Apify and Make, where automation is no longer confined to simple task execution but can also include data extraction, workflow optimization, and intelligent process coordination (Forni et al., 2023).

But the same qualities that make AI beneficial also make it difficult to adopt. Many AI models still operate as "black box" systems, meaning that their judgments are not necessarily straightforward to explain or audit. This causes challenges for enterprises that need transparency, accountability, and regulatory compliance, especially in sensitive fields such as finance, healthcare, and network management (Schemmer et al., 2022). AI systems frequently rely on probability and pattern recognition, which makes their behaviour more difficult to anticipate in every scenario than traditional workflow models, which are typically deterministic (Hemel et al., 2008).

Another important point is that AI automation cannot be applied in the same way across all domains. Healthcare workflows require strong clinical governance, regulatory control, and careful human involvement (Dai & Abràmoff, 2023). Similarly, network automation benefits from AI-driven flexibility, but it also requires backup systems and human supervision because network failures can seriously affect service reliability and security (Tang et al., 2020). These examples show that AI-based workflow automation must be adapted to the risks and requirements of each specific environment rather than treated as a universal solution.

The literature also suggests that modular design is one of the most practical ways to introduce AI into existing workflow systems. Instead of replacing entire platforms, organizations can add AI capabilities through modular components, containerization, and microservices. This makes implementation more manageable and allows AI tools to be integrated gradually into existing infrastructures (Çelik, 2024; Sarkar et al., 2018). Hybrid AI systems that combine machine learning with symbolic reasoning may also help address some current limitations, especially around explainability and verification (Kunz et al., 1984).

Ethical concerns remain another major issue. Although many studies mention fairness, privacy, bias, and accountability, these issues are often treated as secondary rather than central concerns. As AI systems become more involved in decisions that affect people and organizations, ethical design must become a core part of workflow automation research and practice (Koulu, 2020).

Overall, AI offers significant benefits for workflow automation, including improved speed, flexibility, and operational efficiency. Successful AI implementation can boost productivity and even create new business models, but it requires responsible governance, workforce preparedness, and efficient change management (Casati et al., 2019; Guarda et al., 2021). Therefore, AI should not be considered as a one-time technology upgrade, but as a long-term organisational transformation that involves continual monitoring, human engagement, and ethical control (Rane et al., 2024). Standard evaluation measures, long-term workplace effects, and human-AI collaboration models that let businesses benefit from automation while upholding accountability and trust should be the key topics of future research (Garg et al., 2021; Wang, Churchill, Maes, Fan, et al., 2020).

5. Conclusion

AI has the potential to revolutionize modern business workflow automation using tools like Apify and Make. It can enhance capabilities through adaptive decision-making, predictive analytics, and process agility. AI can also resolve issues with traditional systems through flexible, intelligent control, making the future of workflows dependent on AI. However, there are also other challenges that exist in using AI in automation such as generating explanations for the decisions made by AI, integrating multiple systems seamlessly and developing the appropriate ethical standards for the use of AI. As a result, each of the subjects listed above will have to be covered by policy in order to maintain an adequate balance of the rapid development of automation systems' technology with the appropriate amount of human interaction. My research has practical and theoretical implications. Practically, the use of AI in automation will enable companies to either expand or increase the complexity of their existing complex processes while still allowing them to be flexible enough to adapt to changing conditions; however, the successful application of AI to automate processes relies upon the effective management of the limitations of each company's specific industry. My research indicated that there exists a need for more formalized standards to be developed for incorporating AI into workflow automation which would provide direction to the teams that will use these systems in the future. There may be some of the possible avenues of future research that can include the study of hybrid AI systems that combine machine learning with symbolic reasoning, as well as longitudinal studies that investigate the social and technical changes occurring within workplaces resulting from the implementation of automation. In conclusion, as AI continues to evolve its role in automating workflows, AI will become focused on producing complete plans and enhancing the entire process instead of just performing individual tasks. Also, the relationships between AI and other emerging technologies (such as edge computing, federated learning), provide a foundation for designing distributed and context aware automation. Consequently, to achieve the full potential of intelligent workflow automation, the challenges outlined above (including developing an ethics based regulatory framework, developing standard interfaces for interoperable systems and developing collaborative work environment methodologies that involve both humans and AI) need to be addressed.

6. References

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