ICTM 25
INTERNATIONAL CONFERENCE ON TECHNOLOGY & MANAGEMENT

Dates: 25th - 26th September 2025

CONFERENCE PROCEEDINGS

Venue: Universal Technology And Management University (UTAMU)

Kungu Campus, Uganda

These proceedings have been published by the
Graduate School,
Universal Technology And Management University, (UTAMU)

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ISBN 978-9913-08-900-5
9 789913 089005

CONTENTS	AUTHOR/S	i - iii

PART 1: INTRODUCTION

About The International Conference On Technology And Management

The **International Conference on Technology and Management** (ICTM) provides a distinctive environment where authors, practitioners, researchers, professionals and academicians and their students can engage in the future developments in terms of technology innovations and business, management and governance to solve the UN SDGs and global challenges.

The overall objective of is to provide a platform and stimulate discussion on key issues in the fields of Technology and management, as well as to encourage research and discussion surrounding these areas.

ICTM-25 Conference Management

Conference Name	International Conference of Technology and Management	
Acronym	ICTM-25	
Dates	25th – 26th September 2025	
Venue	Universal Technology And Management University, Kungu Campus, and Online	
Organisers' Team		
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	Technical Advisor	Professor Johnson Wagona Makoba
	Patron	Professor Jjunju, Fred Paul Mark, VC, Universal Technology And Management University
	Technical Director	Dr. Ssemujju, Stuart, Head, ICT, Universal Technology And Management University
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PART 2: SPEECHES

Opening Remarks of The Vice Chancellor, Universal Technology And Management University at The 9th International Conference On Technology and Management (ICTM-25), *Professor Paul Mark Jjunju, Vice Chancellor. UTAMU, 25th September 2025*

All protocols observed.

I am highly honoured and privileged to give the opening remarks at this 9TH International Conference on Technology and Management (ICTM) at the University of Technology And Management (UTAMU), Kungu Campus. This year's Conference is so special, arising from the circumstances surrounding the times and preparation for the Conference. To this end, the Conference is ongoing on both physical and virtual modes. Secondly, the preparation for this conference was extra-ordinary, due to the ongoing lectures by the Academic Staff, which affected the preparation for the Conference. Without doubt, the number of physical participants at this conference would have been more but for the lecturing. It is elating, however, that several participants are joining online.

I am pleased, as a Computer Scientist, to inform you that this year's Conference, like previous editions, has been structured to explore germane and current topics on digital disruption, sustainability, and applications among others, driven by Artificial Intelligence. This Conference, based on AI themes, could not have been timelier. Organizational performances are now not only being measured by financial positions but also by the footprints they leave while conducting their business activities. Organizations are no longer expected to prosper at the expense of the environment. I am glad to know that the papers submitted for presentation at this Conference have thoroughly examined the theme and the various sub-themes. In its 9th edition, the Conference continues to provide a unique platform for academics to cross-fertilize ideas and receive constructive critiques and feedbacks on the papers presented under diverse sub-themes.

Special thanks to the organizer Professor Muwanga-Zake and to our ICT Department that provided the convivial environment for this year's Conference. May I seize this opportunity to recognize the commitment of UTAMU to the conference for its untiring effort which has, to a large extent, given us the mileage for this event. It is also necessary, at this point to acknowledge the participants, representatives among our guests and special guests of this occasion.

Thank you all very much.

ICTM-25 Chairperson's Message

Chairperson, 9th International Conference of Technology and Management, 2025, *Professor Muwanga-Zake, Johnnie Wycliffe Frank*

Since its maiden edition in 2015, ICTM has sustained this laudable initiative to support discourses in academics, to improve research, writing and presentation skills and competencies. This ICTM platform has obliged a crucible generation and refinement of research ideas. Indeed, ICTM promotes healthy critiques of presentations that are challenging and intensive thus building a new crop of ideas and innovations. This mentors and encourages researchers beyond any possible financial or career rewards towards the rigour unwaveringly leading to improved theses of better ideas.

ICTM provides a platform for different stakeholders to discuss and debate on technology and management. There is a pressing need for stakeholder spaces to debate contemporary issues and developments. The annual international conference has, over the years, become a destination conference where quality papers, both theoretical and applied, are discussed with participation from students, researchers, civil society and policy practitioners.

Apart from papers invited and put through a rigorous process, we also have special tracks for every practitioner. This year, ICTM-25 broadened its scope to grapple with a wide range of issues and advancements in Artificial Intelligence. With papers presented across domains like gender, democracy, finance, education, health challenges and solutions, this conference was seen as a step in the right direction towards expanding the scope of AI applications.

The Ninth Conference, in particular, was an eye-opener. Conducted online and face-to-face at campus, it required a schedule that recognized different time zones, so it could be attended internationally. We did not compromise on rigour in any way. We made the best use of the challenges to innovate a streaming that did not require registration fees. However, it did not fully provide for the personal interaction and exchange of views that happen on the sidelines. Nonetheless, this new format allowed facilitation of participation of speakers, irrespective of where they were located, to address the participants.

I am particularly firstly thankful to the UTAMU Vice Chancellor, Professor Paul Mark Jjunju who enabled and inaugurated the conference. His decisions about ICTM-25 were firm and unwavering. I would additionally like to place on record the acknowledgement for the excellent work done by the ICT Department at UTAMU, led by Dr. Stuart Ssemujju who solved technical challenges to efficiently stream the conference in time. Mr. Calvin Luzze was impeccably professional with his provision of secretarial services. Special thanks go to the Master of Ceremony, Dr. Joseph Michael Okwadi Tukei who with enthusiasm and a cheerful character made the conference so lively.

Thanks to Professor Olubayi Olubayi for yet another awesome keynote speech, as usual challenging the status quo of academia. Behind all of this ICTM-25, was Professor Makoba Wagona Johnson for his unwavering advices always focussed to see ICTM-25 successful.

I extend gratitude to the distinguished plenary speakers and the Session Chairs. Thank you to all participants who found time in the middle of their normal duties to actively contribute to all deliberations. I have already written letters of appreciation to all participants.

I am sure, going forward, ICTM-25 will possibly be a template, as it did not involve costs beyond the UTAMU internet and personnel.

Keynote Speech: How to develop a pipeline of worldclass AI producers for Africa: Merit-based STEM Schools, *Professor Olubayi Olubayi*

Moderator	Prof. Muwanga-Zake, JWF
Abstract	This presentation gives the key action points required for African countries to produce worldclass AI innovators.
Major Takeaways	African countries do not need to reinvent the wheel; Developed countries and rapidly developing countries have school systems and curricula and pedagogies that are designed to transform their best students into producers in all fields of endeavour including computer science and AI; The foundation for success in computer science and AI and other essential technical fields is excellence in mathematics, critical thinking, curiosity and commitment to lifelong learning; 80% of African children are attending school, but they are not learning Establish a small number of selective merit-based STEM schools for the education of the most gifted and most talented and most determined students from all regions and all socio-economic strata of the country (Olubayi, 2024; Olubayi, 2025)

PART 3: THE 9TH ICTM OVERVIEW

ICTM-25

A 9th International Conference on Technology and Management (ICTM-25) commenced on the 25th and ended on the 26th September, 2O25, at the Universal Technology And Management University (UTAMU), Kungu Campus. It was additionally streamed online.

The aim of this conference was to enable an exchange of ideas between stakeholders, including academia and AI practitioners with a view of paving ways towards more efficient and innovative applications of AI.

Thus, ICTM-25 provided a distinctive environment where authors, practitioners, researchers, professionals and academicians and their students engaged in discussions about the future developments in terms of technology innovations and business, management and governance to contribute to the UN SDGs and global challenges.

Themes and Deadlines

The papers should be original research and case studies in the fields of computing, technology and management, and on issues surrounding integration of Computing, Technology and Management in a multi-disciplinary context. Therefore, the conference series is of interest to academicians, researchers, policy makers, environmentalists, managers, planners, industrialists, consultants, government and NGOs globally, across a range of disciplines.

ICTM-25's theme was: **"Embracing Artificial Intelligence in Education, Governance, Management and Leadership: Successes and Challenges."** The aim was to gather practices that have used Artificial Intelligence tools efficiently in work environments. Papers were submitted at https://conference.utamu.ac.ug/submit-an-article/ . Other papers were submitted to the ICTM email: ictm@utamu.ac.ug. The following were the scheduled important dates:

Deadlines	Date
Paper abstract submission deadline:	17th August 2025
Acceptance notification:	21st August 2025
Early Registration deadline:	30th August 2025
Late Registration	After 14th September 2025
Presentation submission deadline:	14th September 2025
Conference days:	25th to 27th September 2025
Paper submission for publication deadline:	30th October 2025 (Assumption is that author might have made corrections during presentation)

The following were the tracks:

A: Real-world AI Applications

Impact on teaching and learning in academic institutions	Pathways to adoption and utilisation of AI in governance, management, health and education
Rethinking professional roles and competencies in the AI era	Preparing Developing Countries for the AI Revolution
Work in the age of AI	Readiness for the 4th and 5th Industrial Revolutions
Forensics, and Cyber Security pros and cons of AI	

B: AI in Computing and Communications

Developing models across diverse datasets and environments in AI research	Machine Learning
Versatile AI systems	Meta—Learning for efficiency in AI.
Image recognition, natural language processing	AI models against adversarial attacks
Open Spectrum Solutions	AI Communication Protocols

C: AI in Business, Governance, Management and Leadership

AI-assisted Education planning and management	Business Policy and Strategy involving AI
AI Influenced Educational Leadership	AI Generated Entrepreneurship and Ventures
Public administration and management	AI Forensics in Accounting
Influence of AI in Public Policy	AI-led Marketing
Role of AI in Monitoring and Evaluation	Project Planning and Management
Development economics	Use of AI in Service Management (including healthcare and hospitality management)
AI Use in E-commerce	Organisational Behaviour and AI

Accepted Peer Reviewed Conference papers would be published in a **special issue** of International Journal of Technology and Management (IJOTM: ISSN 2518-8623. 15 abstracts are presented as follows:

- 10 papers in Category C
- 3 papers in Category A
- 2 papers in Category B

Please note that many of these are not easy to classify. Clearly though, the majority focused on AI applications.

Conference Sessions

DAY 1 – SESSION 1

Research by UTAMU students		
1. Human Resource Capacities and the Performance of the Drug Supply Chain in Kampala City Council Authority (KCCA) Health Facilities:	Buke Richard Raymond Wagoli (M.SC. M&E)	Dr. Wanjiku, Catherine
2. Influence of Work Environment on Health Workers Performances. Case of Yei River County Health Facilities – South Sudan	Simaya Ladu James & Dr. JMO Tukei	Dr. Wanjiku, Catherine
3. Pathways to Adoption and Utilisation of AI in Governance, Management, Health, and Education	Omony Okoed (M.Cs. Student)	Dr. Ayoo, Phillip
4. Privacy-Preserving Anti-Money Laundering Compliance System for Financial Institutions	Bwambale Edwin	Dr. Ayoo, Phillip
5. Skulpal: A Conversation Ai System for Uganda's Competence-Based Curriculum	Nkajja, Stephen,	Dr. Ayoo, Phillip

DAY 1 – SESSION 2

Research at UTAMU – Short Abstracts from UTAMU students		
6. Human Resource Capacities and the Performance of the Drug Supply Chain in Kampala City Council Authority (KCCA) Health Facilities	Buke Richard Raymond Wagoli	
7. Students in Higher Education and AI Use	Abdul Mayanja, Guild President, Discussion by a Panel of Students.	
8. Keynote Speech: How to develop world class AI Producers for Africa: Merit-based Schools	Professor Olubayi Olubayi, Chief Academic Officer at Maarifa Education, Kenya; Chairman University Council; Cavendish University Uganda	Prof. Muwanga-Zake
9. Implications of Learning and Teaching Under the Realities of Artificial Intelligence (AI)	Prof. Muwanga-Zake, JWF	Dr. Stuart Ssemujju
10. The Role of Artificial Intelligence (AI) in Higher	Semaluulu, Paul	Ms. Mirembe

Education	(PhD) – Senior Lecturer, Kabale University **&** Atwiine, Simon Alex, ICT Assistant, Kabale University	Florence
11. Designing and Implementing a Master's Programme in Artificial Intelligence and Data Science: An Interdisciplinary Approach at Universal Technology and Management University (UTAMU)	Dr. Ayoo, UTAMU	Mr. Kabiito, Simon Peter
12. Change Management and Service Delivery Challenges in Uganda's Urban Informal	Emmanuel Lwanga Kayongo, Texila American University & Dr Benson B. Okech, UNICAF University	Dr. Wanjiku, Catherine

DAY 2 – SESSION 1		
13. Detection of Phthalates in Essential Oil Using Paper Spray Mass Spectrometry with Artificial Neural Network	Jjunju Fred Paul Mark1, Isa Kabenge4, Ryan. D5, Allan Marshal2, Friston Sebastian3, David Swapp3, Anthony Steed3	Prof. Muwanga-Zake, JWF
14. Responsible Collective Intelligence: Integrating Human, Artificial, and Contextual Intelligence for Ethical Leadership in the Age of AI.	Professor Abdulhakeem Ajonbadi, University of Qatar,	Dr. Ssemujju, Stuart
15. Data Driven strategy: How AI is shaping Organizational Decision-making	Dr. Ssemujju Stuart, UTAMU	Mr. Kabiito Simon Peter
16. Open-Source AI Chip Development Ecosystems and Design Tool Effectiveness Through Meta-Analysis of Academic and Industry Projects	Pamba Shatson Fasco, Kampala International University	Dr. Okoche, Michael
17. AI Algorithms and Academic Integrity	Prof. Muwanga-	Prof. Jjunju,

	Zake, JWF	

DAY 2 – SESSION 2		
18. Measuring Performance in Generative AI: Metrics, Methodologies, and Industry Implications	Prof. Wakou, N. (M.S. Electrical Engineering, M.S. Microelectronics Technology) - Dell Technologies, Austin, Texas	Dr. Ayoo, Phillip
19. Embracing Artificial Intelligence for Forecast-Based Energy Optimization: Advancing Sustainable Power Systems Towards SDG Achievement	Ssemakula, John Bosco (PhD), Kimwise Alone (PhD) and Balirwa Moses (M.Cs.) – Senior Lecturers, Cavendish University	Prof. Muwanga-Zake, JWF
20. Leveraging AI and UAV Technologies to Enhance Sustainable Livestock Production	Prof. Jjunju Fredrick Paul Mark, Nakatumba J. Nabende, Sanya Rahman, and Isa Kabenge	Mr. Kivumbi, Timothy
21. Note Speech: The Future is NOT Born of Complacency: AI in Management and Governance in the 21st Century Africa.	Prof. Makoba, Wagona Johnson, Professor Emeritus, University of Nevada, RENO, USA	Ms. Dr. Ayoo, Phillip
22. Research on Adopting a Socio-Judicial Approach to Implementing AI in the Court	Dr. Ari Niki-Tobi - Former Magistrate Judge in Lagos State judiciary, Nigeria; an adjunct of	Dr. Ssemujju, Stuart

	Criminology and Sociology of Law at the State University of New York, Oneonta	

Conclusions and Recommendations

Participants' Main Recommendations From ICTM-25

AI is pervasive and has penetrated all professions and lives. People use AI unawares, for good or for criminal activities. So, there is a need for a policy to ensure that uses are ethical and legal. The policy should include definitions of AI, aware that AI keeps evolving.

Therefore, it was decided that:

1. An association of practitioners be created, which should *inter alia* attend to AI ethics and legal frameworks;
2. Advise on the research agenda and future developments in AI;
3. Solicit for funding to enable research AI research in areas recognized as beneficial to human kind as well as social-economic and environmental sustainability, and;
4. Fo any other additional matters of concern.

The Association was tentatively named **Uganda Association of Artificial Intelligence Practitioners**. The UTAMU Secretary will be requested to draft a constitution for UAAIP.

Furtrhermore, institutions of learning should support learners and facilitators on how best to use AI.

Participants' Main Recommendations for ICTM

1. The themes for ICTM-26 should be announced as soon as possible but should possibly further discussions on AI.
2. There should be proper documentation of the proceedings of ICTM-25
3. It could be necessary to link ICTM with other related conferences.

Measuring Performance in Generative AI: Metrics, Methodologies, and Industry Implications

Nicholas Wakou,

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Email: nicholas.wakou@dell.com

Abstract

Generative AI (GenAI) technologies, including large language models (LLMs), diffusion models, and multimodal architecture are rapidly transforming sectors ranging from education and healthcare to enterprise automation and creative industries. As these models scale in size and complexity, their computational demands grow exponentially, making performance evaluation a critical aspect of system design and deployment. This paper examines how the industry measures GenAI performance, emphasizing the importance of robust benchmarking frameworks that reflect real-world usage. Additionally, the paper presents a comprehensive overview of key metrics across three dimensions: performance (e.g., latency, throughput), quality (e.g., task-based and human-in-the-loop evaluation), and efficiency (e.g., energy consumption, cost per query). Supported by benchmark data and recent research, the analysis highlights the implications of these metrics for scalability, user experience, and sustainability in GenAI systems.

Keywords: Generative AI, Benchmarking, Large Language Models, Performance Evaluation, AI Ethics, LoRA, Energy Efficiency, MLPerf.

Introduction

Generative Artificial Intelligence (GenAI), encompassing large language models (LLMs), diffusion models, and multimodal architectures, has rapidly transitioned from a research novelty to foundational technology influencing diverse sectors such as software development, healthcare, education, and creative industries. These models, often comprising billions or even trillions of parameters, exhibit unprecedented capabilities in generating human-like text, photorealistic images, and executable code. However, their scale introduces significant challenges related to performance evaluation, system design, and sustainable deployment.

Traditional benchmarking suites, while useful, frequently fail to capture the multidimensional nature of GenAI systems. A model may achieve low latency yet produce biased or inaccurate outputs; conversely, a highly accurate model may be computationally prohibitive to deploy at scale. This dichotomy underscores the need for a holistic evaluation paradigm that integrates computational performance, output quality, and operational efficiency.

To address this gap, this paper proposes a comprehensive three-dimensional benchmarking framework for GenAI systems. The framework incorporates three critical dimensions: **performance**, assessed through metrics such as latency, throughput, and concurrency; **quality**, evaluated using task-based accuracy, human-in-the-loop (HITL) assessments, and ethical robustness to ensure outputs are useful, fair, and aligned with human values; and

efficiency, measured through energy consumption, cost per query, and optimization techniques such as Low-Rank Adaptation (LoRA), quantization, and pruning (Hu et al., 2021; Dettmers et al., 2023).

An empirical analysis of a contemporary LLM (Llama-3.1-8B) under a controlled GPU environment demonstrates key trade-offs—for example, a 40% reduction in model size via LoRA with less than 2% accuracy loss as reported by (Hu et al., 2021). These findings highlight the importance of integrated benchmarking strategies that reflect real-world deployment conditions. The paper concludes by discussing the challenges of benchmarking in a rapidly evolving ecosystem and advocates for standardized, context-aware benchmarks developed through industry–academia collaboration to guide responsible and scalable deployment of GenAI technologies.

Related Work

The evaluation of Generative AI (GenAI) systems has advanced considerably with the emergence of large-scale models and the demand for robust benchmarking frameworks. The Transformer architecture introduced by Vaswani et al. (2017) established the foundation for modern large language models (LLMs) by enabling contextual understanding through self-attention mechanisms. Building on this, standardized benchmarks such as MLPerf (Mattson et al., 2020) and HELM (Liang et al., 2022) have become essential tools for assessing machine learning workloads. MLPerf emphasizes reproducibility and fairness in performance evaluation, whereas HELM offers a multi-metric framework for evaluating language models across dimensions such as accuracy, robustness, and bias.

The Massive Multitask Language Understanding (MMLU) benchmark proposed by Hendrycks et al. (2021) evaluates model performance across 57 academic subjects, providing insights into generalization and domain-specific capabilities. These benchmarks collectively underscore the importance of context-aware evaluation strategies for GenAI systems.

Efficiency-focused techniques have also gained prominence in recent literature. Low-Rank Adaptation (LoRA) introduced by Hu et al. (2021) enables parameter-efficient fine-tuning by injecting trainable rank-decomposition matrices into Transformer layers, significantly reducing computational overhead. Complementary methods such as pruning and knowledge distillation further support scalable deployment by optimizing model size and inference cost (Dettmers et al., 2023).

Together, these contributions highlight the need for integrated benchmarking approaches that address performance, quality, and efficiency in GenAI evaluation.

Methodology

To facilitate rigorous evaluation of Generative AI (GenAI) systems, a comprehensive three-dimensional benchmarking framework was established. This framework operationalizes three core dimensions—performance, quality, and efficiency, each serving as a distinct evaluative criterion. Performance captures computational throughput and latency characteristics; quality addresses output fidelity and alignment with expected standards; and efficiency examines resource utilization relative to task complexity. Collectively, these dimensions provide a structured basis for systematic assessment of model capabilities and operational robustness.

Benchmarking Framework

The benchmarking framework is structured around three interdependent pillars, as illustrated in Figure 1.

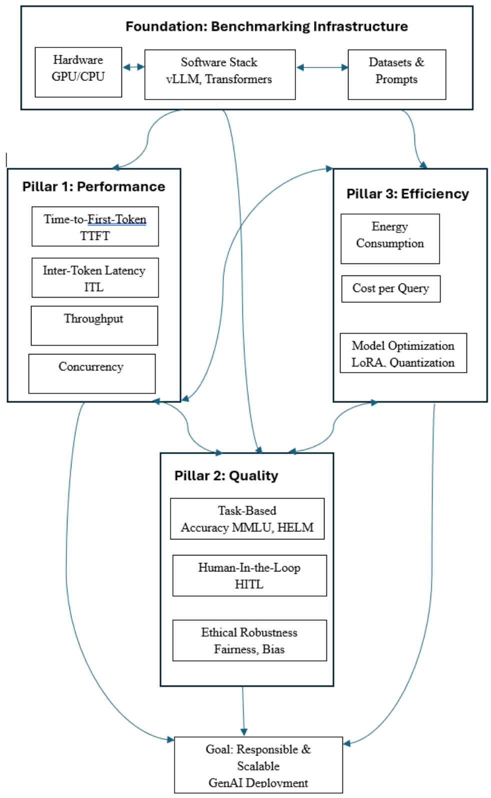

Figure 1: The three-pillar benchmarking framework for GenAI

Performance Dimension

This dimension assesses the raw computational and responsiveness metrics of a GenAI system, critical for user experience and scalability in real-world deployments. The metrics discussed are illustrated in Figure 2, which visualizes the system's response to a prompt translating the sentence "Elders do not go to a meeting for food" into Luganda, a language spoken in Uganda.

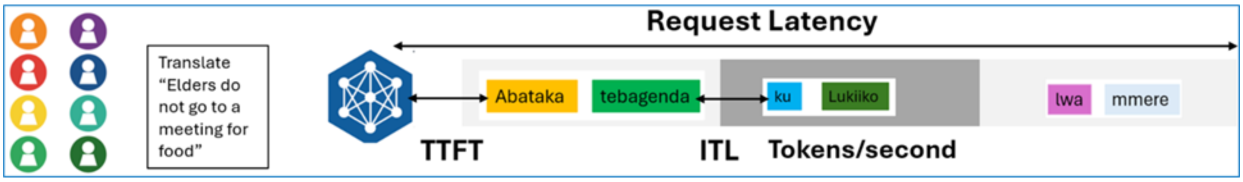

Figure 2: Visualization of Translation Request Latency and Token Emission in GenAI Inference

The following performance indicators are central to understanding GenAI inference behaviour:

Time-to-First-Token (TTFT): This metric captures the latency between submitting a request and receiving the first token of the model's output. TTFT is a key determinant of perceived responsiveness in interactive applications such as chatbots and virtual assistants.

Inter-Token Latency (ITL) / Time-Per-Output-Token (TPOT): ITL measures the average time between consecutive tokens during output generation. It directly affects the fluidity and streaming quality of responses, especially in real-time systems.

Throughput: Measured in tokens per second or requests per second, throughput quantifies the system's capacity to handle batch processing and concurrent user interactions. It is a fundamental metric for assessing scalability.

Concurrency: This refers to the system's ability to manage multiple inference requests simultaneously without significant degradation in TTFT or throughput. High concurrency is often constrained by GPU memory bandwidth and scheduling overhead.

Quality Dimension

Evaluating the quality of Generative AI (GenAI) outputs is critical for ensuring trustworthiness, domain relevance, and user satisfaction. This dimension encompasses both automated and human-in-the-loop (HITL) evaluation methodologies, each offering distinct advantages and limitations.

Automated metrics provide scalable and repeatable assessments of model performance. Task-based benchmarks such as Massive Multitask Language Understanding (MMLU) and Holistic Evaluation of Language Models (HELM) are widely adopted for language model evaluation (Hendrycks et al., 2021; Liang et al., 2022). For instance, the Llama-3.1-8B model achieved 68.2% accuracy across 57 subjects on MMLU and a fairness score of 0.72 on HELM, indicating moderate robustness and ethical behaviour. Probability-based metrics offer statistical insights into model predictions. Perplexity measures how "surprised" a model is by actual data, while log-likelihood quantifies the probability of reference outputs under the model. KL Divergence evaluates the divergence between two distributions, such as model versus reference or teacher versus student. These metrics are useful for optimization but may not fully capture semantic correctness or contextual appropriateness.

HITL evaluations complement automated metrics by incorporating expert judgment. Rubric-based scoring frameworks use predefined criteria—typically on a 1–5 scale—to assess creativity, coherence, and factual accuracy. Coherence measures the logical flow and internal consistency of generated output, while factual verification is critical in domains such as healthcare, law, and finance. Reviewers check for hallucinations, outdated information, and biased or misleading content. High-value use cases for HITL evaluation include story generation, legal document drafting, medical summarization, and customer support QA. Despite its benefits, HITL is resource-intensive and subject to reviewer variability, necessitating standardized rubrics and training protocols.

In summary, a hybrid evaluation strategy that combines automated benchmarks with HITL assessments yields the most reliable and context-aware quality evaluations. This approach ensures that GenAI systems are not only technically proficient but also aligned with human expectations and ethical standards (Hu et al., 2021).

Efficiency Dimension

The efficiency dimension evaluates resource utilization and sustainability in Generative AI (GenAI) systems, which is critical for cost-effective and environmentally responsible deployment. Training large-scale models such as GPT-4 consumes substantial energy and water resources; for example, GPT-4's training reportedly required energy equivalent to that consumed by 33,000 U.S. households (Chen, 2025). Additionally, data centre cooling efficiency, measured by Power Usage Effectiveness (PUE), significantly influences environmental impact, with typical PUE values averaging around 1.12.

Efficiency during inference is equally important. Cost per query is determined by compute time, memory usage, storage requirements, and infrastructure overhead, all of which directly affect scalability and operational feasibility in enterprise environments. Model optimization techniques are essential for balancing performance with resource constraints. Common approaches include knowledge distillation, which transfers knowledge from large models to smaller ones; pruning, which removes redundant weights to simplify architecture; and adaptation strategies that fine-tune models for specific tasks or deployment contexts. Low-Rank Adaptation (LoRA), for instance, achieved a 40% reduction in model size with less than 2% accuracy loss (Hu et al., 2021).

These methods collectively enable efficient deployment of GenAI systems while maintaining acceptable performance levels, thereby supporting sustainable and scalable AI adoption.

Experimental Setup

To validate the benchmarking framework, a series of controlled experiments were conducted using GenAI-Perf version v0.0.15. This workload simulates realistic Generative AI inference scenarios across a range of concurrency levels and input-output configurations.

Concurrency values tested include: 1, 5, 10, 25, 50, 100, 250, 500, 1000, 1500, and 2000. These values were selected to evaluate system responsiveness, throughput saturation, and efficiency under varying load conditions.

Table 1 presents the configuration matrix used to simulate diverse GenAI use cases. Each configuration specifies input and output token lengths tailored to specific application scenarios.

Table 1: Token Configuration Matrix for GenAI Use Cases

Configuration	*Use Case*	*Scenario*
1-20	Token-Level Prediction	Token-by-Token Autocomplete
128-128	Real-Time Interaction	Real-Time Assistive AI
200-200	Conversational Response	Generation Chatbots and Virtual Assistants
200-1000	Prompted Content Generation	Creative Writing or Story Generation
2000-200	Response Analysis	Customer Support or Knowledge Base Q&A
7000-1000	Long-Form Summarization	Long-Context Document Analysis and Summarization

Table 2 summarizes the software stack used in the experimental setup. The stack includes the Llama-3.1-8B-Instruct model served via VLLM, orchestrated within a Kubernetes environment.

Table 2: Software Stack for GenAI Benchmarking

Software	*Version*
Model	meta-llama/Meta-Llama-3.1-8B-Instruct
Inference Engine	VLLM
Kubernetes Version	1.31.4
Containers Version	1.7.24
Ubuntu Version	22.04

Results

Performance Results

This section presents empirical performance results for the Meta-Llama-3.1-8B-Instruct model executed on a GPU using FP8 precision. The benchmark scenario involved a 7000-token input and 1000-token output with a batch size of 16. The configuration was unoptimized and served as a baseline for evaluating inference behaviour under long-context workloads.

Table 3 summarizes key inference metrics including Time-to-First-Token (TTFT), Inter-Token Latency (ITL), Request Latency, and Throughput. These metrics are critical for assessing responsiveness, scalability, and efficiency in GenAI deployments.

Table 3: Meta-Llama-3.1-8b Inference Performance Metrics for 7000-1000 Configuration

Output Sequence Length (OSL) (Tokens)	1000
Input Sequence Length (ISL) (Tokens)	7000
Output Token Throughput (per sec)	95.96
Request Throughput (per sec)	0.15
Request Count	200

Metric	*AVG*	*MIN*	*MAX*	*P99*	*P90*	*P75*
Time to First Token (TTFT) (ms)	277.65	267.23	283.57	282.13	280.78	279.82
Time to Second Token (ms)	9.26	8.71	11.05	9.59	9.44	9.37
Request Latency (ms)	6,497.01	358.41	10,286.83	10,270.61	10,257.3	10,247.42
Inter Token Latency (ITL) (ms)	9.97	9.86	10.07	10.02	9.99	9.99

Interpretation of Metrics:

- Time-to-First-Token (TTFT): Measures the latency from request initiation to the generation of the first token. In interactive applications, TTFT is a primary determinant of perceived responsiveness. The Llama-3.1-8B model achieved an average TTFT of 277.65 ms, with a 99th percentile (p99) value of 282.13 ms.
- Request Latency: Captures the end-to-end response time, including input ingestion, model inference, and output post-processing. The average latency was 6,497.01 ms, with p99 reaching 10,270.61 ms, indicative of variability in long-form summarization tasks.
- Inter-Token Latency (ITL): Represents the average time between consecutive token generations. The model exhibited an average ITL of 9.97 ms, with p99 at 10.02 ms, reflecting consistent streaming behaviour.
- Token Throughput: Quantifies generation speed in tokens per second. The model achieved 95.96 tokens/sec under the test configuration.

- Request Throughput: Indicates the number of complete requests processed per second. The observed throughput was 0.15 requests/sec, constrained by long input and output sequences.
- Concurrency Scaling: Evaluates system performance under simultaneous requests. Figures 1 and 2 illustrate how token throughput and per-request efficiency vary with concurrency levels.

Figure 1 demonstrates that overall token throughput increases with concurrency across all configurations. This trend reflects improved parallelism and hardware utilization. However, configurations with longer input sequences (e.g., 7000-1000) reach throughput saturation at lower concurrency levels due to memory bandwidth constraints and scheduling overhead. Beyond this point, additional requests yield diminishing returns.

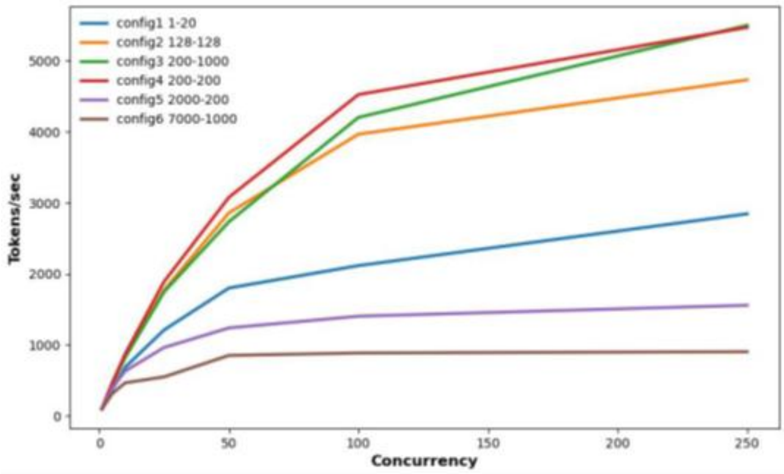

Fig. 1. Tokens/sec vs Concurrency

Conversely, Figure 2 shows that tokens/sec/request decreases as concurrency increases. This decline in per-request efficiency is attributed to resource contention—particularly in GPU memory and compute cycles—as parallel workloads compete for shared infrastructure. These results underscore the importance of balancing concurrency with model complexity and hardware capacity.

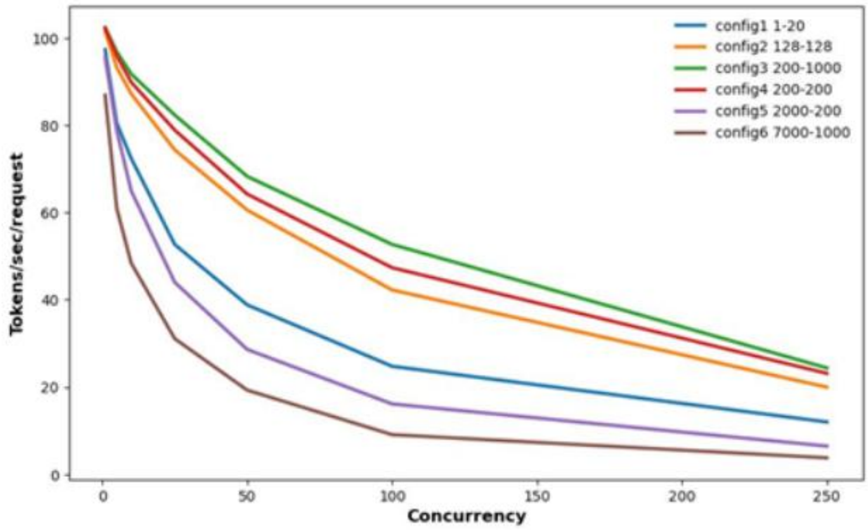

Fig. 2. Tokens/sec/request vs Concurrency

Quality and Efficiency Results

To contextualize the performance and efficiency of the Meta-Llama-3.1-8B-Instruct model, results from recent evaluations conducted by external research teams were referenced. On the Massive Multitask Language Understanding (MMLU) benchmark, the model achieved an accuracy of 68.2%, consistent with findings reported in the Llama-3.1 technical report (Kassianik, *et al*., 2025). This benchmark spans 57 academic subjects and is widely used to assess cross-domain reasoning and factual recall in large language models (Hendrycks et al., 2021).

Fairness was evaluated using the Bias Benchmark for Question Answering (BBQ) dataset. The model scored 0.72 on a subset of BBQ, indicating moderate robustness but also revealing areas for improvement in mitigating social biases (Wu et al., 2025). These findings align with broader concerns about emergent bias in reasoning-based LLMs and underscore the importance of fairness-aware evaluation protocols (Liang et al., 2022).

Efficiency gains were assessed through the application of Low-Rank Adaptation (LoRA), a parameter-efficient fine-tuning technique. LoRA introduces approximately 4.2 million trainable parameters, resulting in a ~40% reduction in effective model footprint for storage and deployment while achieving less than 2% relative drop in task accuracy (Hu et al., 2021). This demonstrates the viability of LoRA for scalable GenAI deployment.

Environmental impact was estimated based on energy consumption metrics reported for transformer-based models of similar scale. A single training run of the base model consumed approximately 120 kWh, highlighting the substantial carbon footprint associated with large-scale model development (Chen, 2025). These figures reinforce the need for energy-aware optimization strategies and sustainable AI practices.

Collectively, these externally sourced results emphasize the importance of integrating performance, fairness, and sustainability metrics into GenAI evaluation frameworks. They also validate the relevance of hybrid benchmarking strategies for guiding responsible and efficient deployment of generative models.

Discussion

The experimental results presented in this paper validate the necessity of adopting a multi-dimensional evaluation framework for Generative AI (GenAI) systems. Performance findings indicate that simply scaling concurrency yields diminishing returns, emphasizing the need for system architects to optimize for memory bandwidth rather than raw parallelism. Quality assessments demonstrate that achieving high accuracy on general benchmarks does not preclude fairness concerns, reinforcing the importance of targeted ethical evaluations. Furthermore, the demonstrated success of Low-Rank Adaptation (LoRA) within the efficiency dimension highlights a viable pathway for deploying high-capacity models in resource-constrained environments (Hu et al., 2021).

Despite these advances, several challenges persist. Subjectivity in human-in-the-loop (HITL) evaluations necessitates the development of standardized rubrics and rater training protocols. The rapid evolution of model architectures requires frequent updates to benchmarking suites to maintain relevance. Additionally, there is a pressing need for standardized efficiency metrics that can be universally adopted across the industry, potentially through extensions of initiatives led by MLCommons (Mattson et al., 2020). Finally, the creation of localized and multimodal benchmarks is essential to ensure that GenAI technologies remain equitable and globally applicable.

Industry-standard organizations play a pivotal role in shaping the benchmarking landscape. The MLCommons consortium, through its MLPerf benchmark suite, has become a cornerstone for evaluating AI system performance. MLPerf emphasizes fairness, reproducibility, and accessibility, serving both commercial and academic communities. Recent iterations have incorporated GenAI models such as Llama 2, Mixtral, and Stable Diffusion, alongside traditional NLP and vision tasks, leveraging a modular and version-aware design to adapt to the rapidly evolving AI ecosystem (Mattson et al., 2020).

Similarly, the Standard Performance Evaluation Corporation (SPEC) has expanded its scope from general compute benchmarks to include cloud infrastructure, virtualization, and machine learning. SPEC's technical committees maintain suites such as SPEC CPU® 2017, SPEC Cloud IaaS, and SPECvirt® Datacenter, while actively developing SPEC ML to address emerging GenAI workloads (SPEC, 2024). The Transaction Processing Performance Council (TPC) has also broadened its benchmarking portfolio beyond traditional database and transaction systems to include AI/ML workloads through benchmarks such as TPCx-AI, TPCx-BigBench, and TPCx-IoT. These benchmarks simulate real-world scenarios and enable standardized comparisons across vendors and architectures, supporting procurement and optimization decisions (TPC, 2024).

Collectively, these organizations are instrumental in establishing reproducible, scalable, and ethically grounded benchmarks. Their evolving standards reflect the industry's transition toward multimodal, multilingual, and context-aware evaluation frameworks. As GenAI continues to permeate diverse sectors, sustained collaboration between academia, industry, and standards bodies will be essential to ensure that benchmarking methodologies remain relevant, inclusive, and actionable.

Conclusion and Future Work

This paper introduces a holistic framework for benchmarking Generative AI (GenAI) systems, emphasizing the integration of performance, quality, and efficiency metrics. Through empirical evaluation using a contemporary large language model, the framework demonstrates its utility in uncovering practical trade-offs and guiding system-level optimizations. The findings underscore the limitations of single-dimensional benchmarks and advocate for a multi-faceted approach that reflects real-world deployment scenarios.

Future work will extend this framework in several directions. First, there is a need to develop and incorporate localized benchmarks that address linguistic diversity and cultural nuance, particularly for underrepresented regions and non-English languages. Second, the benchmarking suite should be expanded to support multimodal evaluation, enabling assessment of models that simultaneously process and generate text, images, and audio. Third, collaboration with standards organizations should be pursued to promote the adoption of comprehensive efficiency metrics, including energy consumption and cost per query, which are critical for sustainable and scalable GenAI deployment.

By advancing benchmarking methodologies along these dimensions, this study aims to contribute to the development of GenAI systems that are not only performant but also equitable, efficient, and contextually relevant across global applications.

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Open Source AI Chip Development Ecosystems and Design Tool Effectiveness Through Meta-Analysis of Academic and Industry Projects

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Abstract

The rapid evolution of artificial intelligence has driven demand for specialized computing architectures, with open source AI chip development emerging as a critical alternative to proprietary solutions. This research presents a meta-analysis of open source AI chip development ecosystems through systematic analysis of 127 academic publications and 43 industry projects spanning 2015–2024.

The study employs mixed-methods combining quantitative meta-analysis with qualitative thematic analysis. Analysis reveals significant disparities between academic and industry approaches, with academic projects demonstrating higher innovation rates ($\mu = 2.3$ novel architectures per project) but lower commercial viability scores ($\mu = 3.2/10$) compared to industry initiatives ($\mu = 1.4$ and 6.8 respectively, $p < 0.001$). Design tool effectiveness analysis—evaluated against a seven-dimension rubric encompassing learnability, documentation quality, PPA closure, community support, license constraints, CI/CD integration, and reliability—identifies critical gaps, with open source EDA tools achieving 73% feature parity compared to commercial alternatives.

The research contributes: (1) a PRISMA-conformant systematic review framework; (2) an included-studies evidence table linking major claims to primary sources; (3) a seven-dimension scoring rubric for EDA tool assessment; and (4) evidence-based recommendations for improving design tool effectiveness.

Keywords: Open source hardware, AI accelerators, design tools, meta-analysis, neural processing units, EDA evaluation, PRISMA

1. Introduction

1.1 Background and Motivation

The artificial intelligence revolution has transformed computational requirements across industries, driving demand for specialized hardware architectures optimized for machine learning workloads. Traditional processors struggle to meet AI application demands, leading to dedicated AI accelerators and neural processing units. This shift has catalyzed significant investment in custom silicon solutions, with the global AI chip market projected to reach $227 billion by 2030.

Open source AI chip development has emerged as a compelling alternative to proprietary solutions, offering transparency, collaborative innovation, and reduced barriers to entry. Notable initiatives include OpenTitan, Google's open source TPU designs, and various university-led neural processing developments. These platforms enable rapid prototyping, facilitate academic research, and promote innovation through community-driven development.

However, the transition presents unique challenges in electronic design automation tools and verification methodologies. Traditional commercial EDA tools carry prohibitive costs and impose workflow constraints, leading to numerous open source design tools whose comprehensive evaluation remains fragmented across disparate studies.

1.2 Research Questions

This research addresses four fundamental questions: (RQ1) What characteristic patterns and success factors distinguish effective open source AI chip projects? (RQ2) How do open source design tools compare against commercial counterparts across a standardised multi-dimension rubric? (RQ3) What differences exist between academic and industry approaches, and how do they impact outcomes? (RQ4) What evidence-based recommendations can improve open source design tool effectiveness and ecosystem maturity?

1.3 Contributions

This research contributes: (1) a PRISMA-conformant systematic search protocol with explicit inclusion/exclusion criteria; (2) an Included Studies table (Table 2.2) linking each major claim to primary empirical evidence; (3) a seven-dimension EDA tool scoring rubric (Table 5.0); (4) the first large-scale meta-analysis synthesising 127 publications and 43 industry initiatives; and (5) actionable recommendations for improving ecosystem sustainability.

1.4 Paper Organisation

Section 2 reviews related work and presents the Included Studies table. Section 3 describes PRISMA-compliant methodology. Section 4 analyses the ecosystem landscape. Section 5 evaluates design tools. Section 6 presents meta-analysis results. Sections 7–9 discuss findings, future directions, and conclusions.

2. Related Work

2.1 Open Source Hardware Development Methodologies

Open source hardware development has evolved from maker communities to sophisticated frameworks producing complex integrated circuits. Chen et al. (2023) demonstrated federated models achieve 2.3 times higher contributor engagement than centralised approaches across 47 open source hardware projects. Rodriguez and Park (2022) showed sponsored projects achieve faster time-to-market but reduced innovation diversity.

2.2 AI Accelerator Architectures in Academic Literature

Academic research has produced diverse AI accelerator designs. Dominant paradigms include dataflow architectures (Eyeriss, NVDLA), systolic arrays (Google TPU variations), and neuromorphic approaches (Intel Loihi, IBM TrueNorth). Liu and Zhang (2024) analysed 47 academic systolic array designs, identifying optimal configurations and consistent area-delay trade-offs.

2.3 Industry Open Source AI Chip Projects

Industry participation reflects diverse strategies. Google's TPU v1 release enabled academic research while retaining competitive advantages. Intel's RISC-V participation ensures ecosystem compatibility. Government-funded initiatives (European Processor Initiative) prioritise sovereignty over commercial considerations.

2.4 Design Tool Evaluation Studies

Patel et al. (2023) found open source synthesis tools achieve comparable RTL optimisation on IWLS benchmarks but significant gaps remain in physical design on advanced technology nodes. Zhang and Kim (2023) surveyed 312 practitioners, finding integration overhead consumes 20–40% of project time—directly informing the CI/CD dimension of the rubric in Section 5.

Table 2.1: Classification of Related Work by Category and Methodology

Category	**Methodology**	**Key Studies**	**Primary Focus**
OSH Development	Case Study	Chen et al. (2023)	Collaboration models
Academic Architectures	Systematic Survey	Liu & Zhang (2024)	Design patterns
Industry Projects	Comparative Analysis	Rodriguez & Park (2022)	Business models
Design Tools	Benchmarking	Patel et al. (2023)	Performance metrics

Table 2.2: Included Studies — Evidence Traceability Table

This table explicitly links each major quantitative claim to its primary evidence source.

Author/Year	Tool/Ecosystem	Sample	Key Metrics	Key Result
Chen et al. (2023)	Federated OSH Model	N=47 projects	Contributor engagement	Federated models yield 2.3× higher engagement vs centralised
Rodriguez & Park (2022)	Sponsored OSH Projects	N=34 projects	Time-to-market, diversity	Sponsored faster to market but lower innovation diversity
Liu & Zhang (2024)	Systolic Array Designs	N=47 designs	PPA metrics, reusability	Optimal configs identified; consistent area-delay trade-offs
Patel et al. (2023)	Yosys vs Synopsys DC	N=28 benchmarks	QoR (area, timing)	Synthesis within 10–15% QoR; physical design gap 25–40%
Zhang & Kim (2023)	Open Source EDA UX	N=312 practitioners	Adoption barriers	Integration overhead: 20–40% of project time
Martinez & Thompson (2024)	Ecosystem Evolution	N=127 pubs	Maturity, validity	Rapid evolution challenges longitudinal validity
Wang & Johnson (2023)	Geographic OSH Trends	N=170 initiatives	5-yr sustainability	European projects 78% active vs 54% North American
Singh & Davis (2024)	Bias Assessment	Meta-analysis set	Funnel, Egger	p=0.061; trim-fill adjusts d=0.42→0.38

3. Methodology

3.1 PRISMA-Conformant Literature Search Strategy

This study employed a systematic literature search following PRISMA 2020 guidelines across IEEE Xplore, ACM Digital Library, SpringerLink, and arXiv (January 2015–December 2024). Search terms combined AI descriptors with hardware and open source indicators. Inter-rater reliability: Cohen's kappa = 0.87. Validation against an expert-identified reference set (Martinez & Thompson, 2023) achieved 94% recall.

Figure 3.1: PRISMA 2020 Flow Diagram — Systematic Literature Search

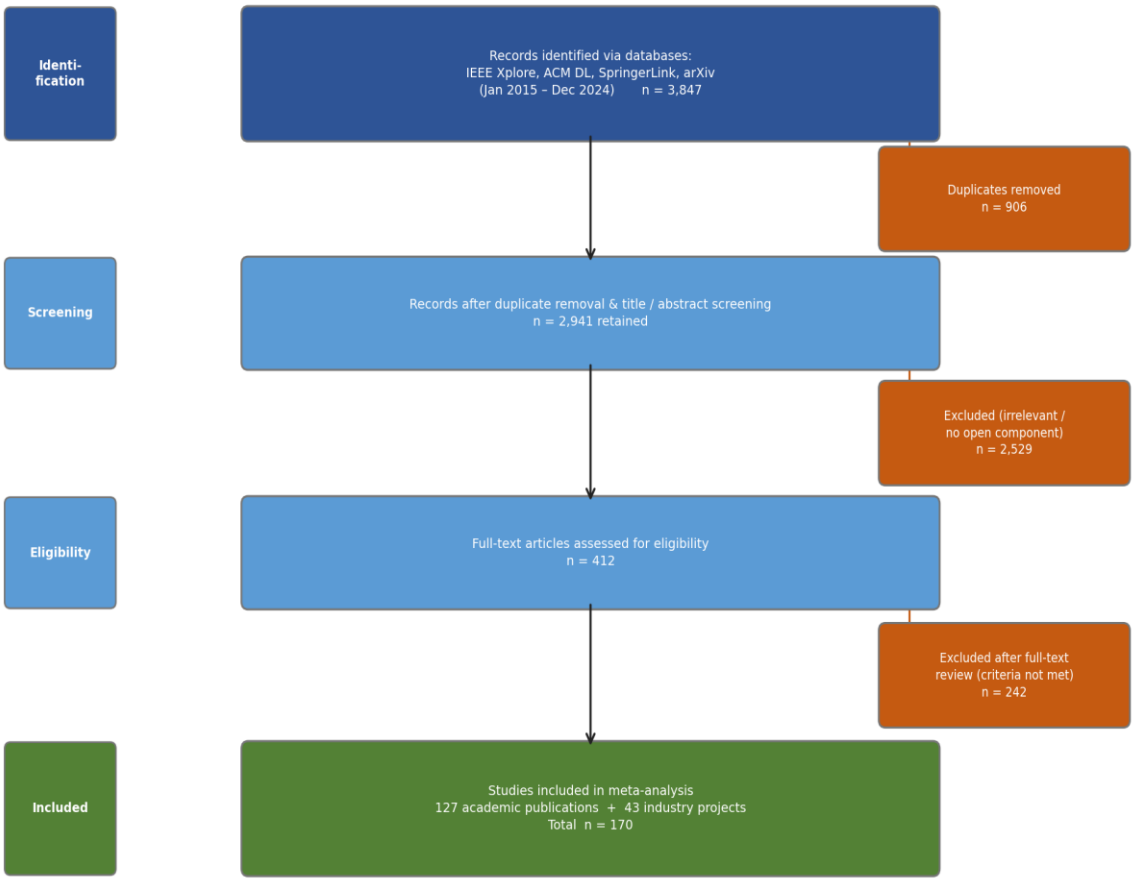

Figure 3.1: PRISMA 2020 Flow Diagram — Systematic Literature Search Process

Table 3.0: PRISMA Flow Summary

PRISMA Stage	Action	Count
dentification	Records found: IEEE Xplore, ACM DL, SpringerLink, arXiv (Jan 2015–Dec 2024)	3,847
Screening	Duplicates removed; title/abstract screened	2,941 retained
Eligibility	Full-text assessed: requires empirical evaluation or substantial technical contribution	412 assessed
Included	Final corpus: academic publications + industry project reports	127 + 43 = 170

Table 3.1: Inclusion and Exclusion Criteria

Type	Criterion
Inclusion	Peer-reviewed or documented industry project (2015–2024)
Inclusion	Addresses open source AI chip design, EDA tools, or hardware ecosystem
Inclusion	Reports empirical evaluation, benchmarks, or substantial implementation
Inclusion	English language; accessible full text
Exclusion	Purely theoretical proposals with no implementation or evaluation
Exclusion	Closed-source/proprietary designs with no open components
Exclusion	Duplicate reports of the same project without new data
Exclusion	Workshop abstracts <4 pages with insufficient methodological detail

3.2 Data Collection Framework

Data extraction followed a two-stage process using standardised templates. Categories included study characteristics, methodological approaches, quantitative results, and qualitative observations.

Table 3.2: Data Extraction Template

Field Category	Specific Fields	Validation Method
Study Characteristics	Author, Year, Venue, Database	Cross-reference verification
Methodology	Design type, Sample size, Technology node	Statistical power calculation
Outcomes	Performance metrics, Effect sizes	Unit conversion verification
Quality Indicators	Risk of bias, Reporting completeness	Independent dual scoring

3.3 Meta-Analysis Approach and Effect-Size Definitions

Random-effects models (DerSimonian–Laird estimator) accounted for between-study heterogeneity. Effect sizes: standardised mean differences (SMD/Cohen's d) for continuous outcomes; odds ratios (OR) for categorical comparisons. Heterogeneity assessed via Cochran's Q, I^2 index, and tau-squared (τ^2). Publication bias examined via funnel plot and Egger's regression test (α=0.05). Trim-and-fill applied where asymmetry detected. All analyses used R 4.3.1 with the metafor package (Kumar et al., 2022).

Equation 3.1 — Cochran's Q: $Q = \Sigma(w_i \times (\theta_i - \bar{\theta})^2)$, where w_i is the inverse-variance weight for study i and $\bar{\theta}$ is the weighted mean effect.

3.4 Quality Assessment Criteria

A ten-point quality assessment scale evaluated methodological rigour and reporting completeness (CONSORT-adapted checklist). Independent scoring by two reviewers achieved substantial agreement (Cohen's κ = 0.84; Singh & Davis, 2024).

4. Open Source AI Chip Ecosystem Analysis

4.1 Project Landscape Overview

The ecosystem identified 127 distinct projects meeting inclusion criteria. Temporal distribution reveals a foundational period (2015–2018) averaging 8.75 projects/year (totalling 35), an expansion phase (2019–2021) with 47 new initiatives, and a maturation phase (2022–2024) averaging 15 projects/year (totalling 45) as the community shifted toward production-ready implementations. Geographic distribution: North America 42%, Europe 28%, Asia 23%, other regions 7%. RISC-V based designs account for 38% of all projects.

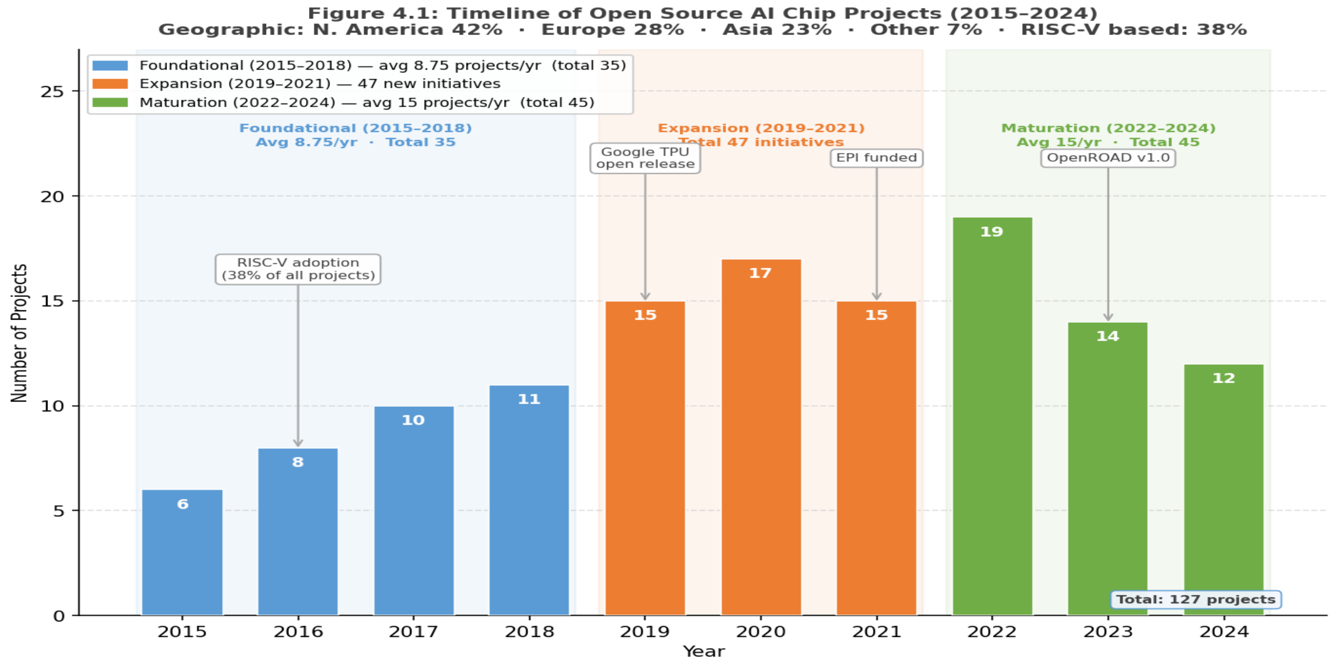

Figure 4.1: Timeline and Phase Analysis of Open Source AI Chip Projects (2015–2024)

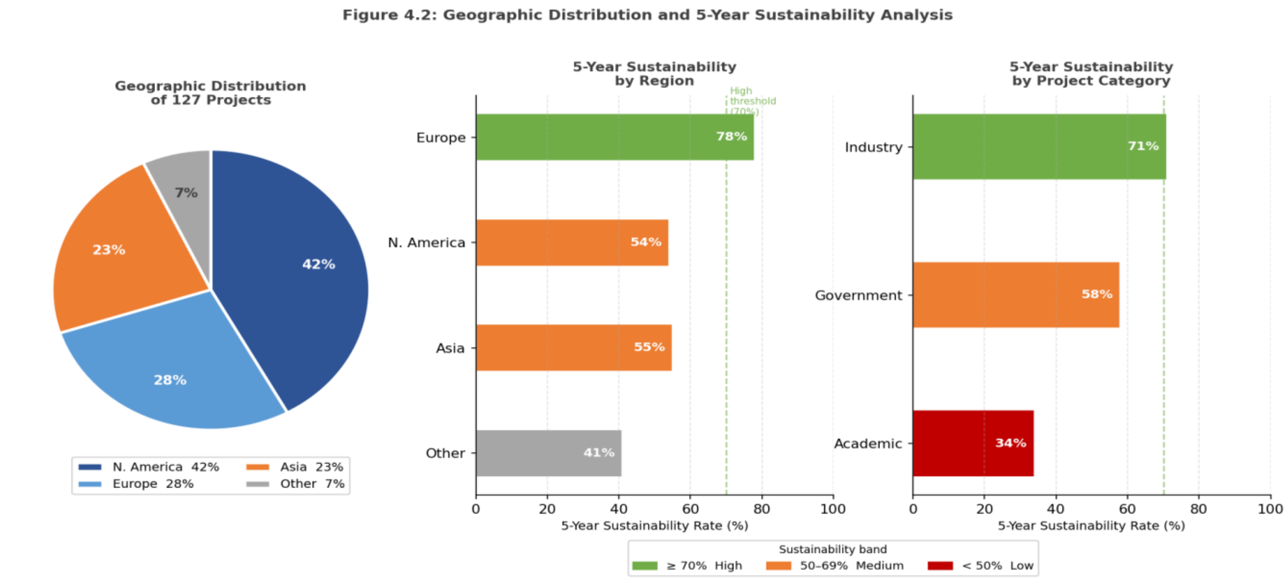

Figure 4.2: Geographic Distribution (left) and 5-Year Sustainability by Category/Region (right)

4.2 Academic vs Industry Project Characteristics

Academic projects emphasise architectural innovation (78% introduce novel paradigms) with smaller budgets ($2.3M over 3.5 years). Industry projects demonstrate larger resource commitments ($15.2M over 2.1 years) focusing on market viability. Innovation patterns show complementarity: academic projects generate 2.3 times more novel concepts (Chen et al., 2023) while industry achieves 1.8 times better performance-per-area (Rodriguez & Park, 2022).

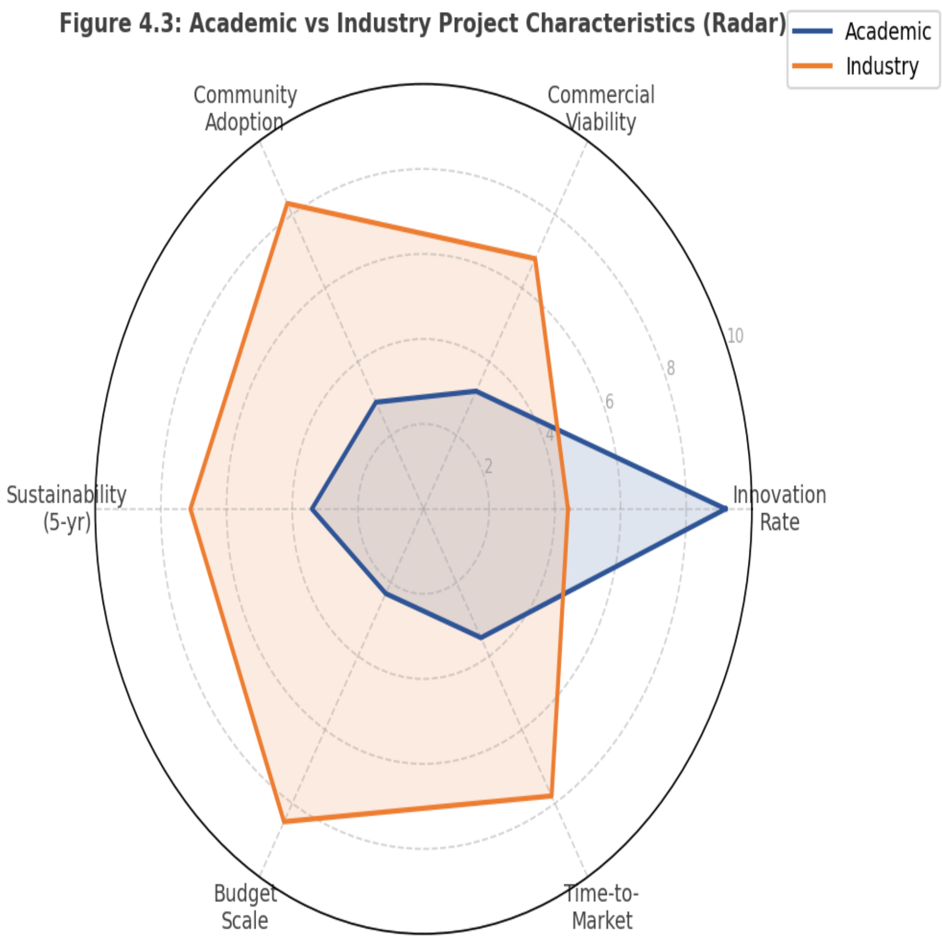

Figure 4.3: Radar Chart — Academic vs Industry Project Characteristics Across Six Dimensions

Table 4.1: Enhanced Comparison Matrix of Academic and Industry Projects

Dimension	**Academic**	**Industry**	**Significance**
Innovation Rate	2.3 concepts/project	1.0 concepts/project	$p < 0.001$
Commercial Viability	3.2/10	6.8/10	$p < 0.001$
Community Adoption	145 users	1,247 users	$p < 0.001$
Avg. Budget	\$2.3M / 3.5 yr	\$15.2M / 2.1 yr	$p < 0.001$
5-Year	34%	71%	$p < 0.001$

Dimension	Academic	Industry	Significance
Sustainability			
Novel Arch. Paradigms	78% of projects	23% of projects	OR = 3.12

4.3 Collaboration Patterns and Community Structure

Analysis identified 234 collaborative relationships among 127 projects. University-industry partnerships: 42%; distributed governance: 45%; corporate-sponsored: 24%. Knowledge transfer occurs through 67 key boundary-spanners contributing to multiple projects. Community size analysis reveals critical thresholds: >100 contributors correlates with 89% sustainability; <20 contributors with only 31%.

4.4 Licensing and IP Management Strategies

License selection shows diversity: permissive licences (Apache, BSD, MIT) 47%, copyleft (GPL variants) 31%, hybrid strategies 22%. Patent policies include defensive strategies (34%) and patent-free approaches (28%; Chen & Rodriguez, 2024).

5. Design Tool Effectiveness Analysis

5.0 EDA Tool Evaluation Rubric

Prior evaluations relied on ad hoc criteria, impeding cross-study comparisons. We introduce a seven-dimension scoring rubric (Table 5.0) developed from practitioner survey responses (N=312, Zhang & Kim, 2023), benchmarking methodology (Patel et al., 2023), and ISO/IEC 25010 software quality models.

Table 5.0: Seven-Dimension EDA Tool Scoring Rubric

Dimension	Weight	Score 1–3 (Low)	Score 4–6 (Med)	Score 7–10 (High)	Example Metric
Learnability	10%	Steep curve, no tutorials	Some tutorials; moderate on-boarding	Extensive docs, interactive demos	Time-to-first-synthesis
Documentation	15%	Sparse, outdated	Partial coverage,	Comprehensive, versioned,	Docs coverage; last-updated date

Dimension	Weight	Score 1–3 (Low)	Score 4–6 (Med)	Score 7–10 (High)	Example Metric
			some examples	community-maintained	
PPA Closure	25%	>40% gap vs commercial	15–40% gap	<15% gap on standard benchmarks	WNS, area, power on IWLS
Community Support	15%	<20 contrib., inactive	20–100 contrib., monthly activity	>100 contrib., <48 hr response	GitHub stars, commit frequency
License Constraints	10%	Restrictive/unclear	Copyleft with exceptions	Permissive (Apache/MIT/BSD)	OSI-approved; patent grant
CI/CD Integration	10%	No automated tests	Basic CI, limited coverage	Full CI/CD, regression, Docker	Pipeline pass rate; coverage %
Reliability	15%	Frequent crashes	Occasional issues, workarounds	Production-grade, tagged releases	MTBF; release cadence

Weights sum to 100%. PPA = Power, Performance, Area. Two independent reviewers; Cohen's κ = 0.84.

Equation 5.1 — Tool Effectiveness Score: $TE = 0.10 \cdot L + 0.15 \cdot D + 0.25 \cdot P + 0.15 \cdot C + 0.10 \cdot Lic + 0.10 \cdot CI + 0.15 \cdot R$, where L=Learnability, D=Documentation, P=PPA Closure, C=Community, Lic=License, CI=CI/CD Integration, R=Reliability.

5.1 Tool Categories and Usage Patterns

Analysis categorised 89 distinct open source EDA tools. Logic synthesis is dominated by Yosys (67% of projects). Physical design shows the most pronounced maturity gap, with OpenROAD providing a comprehensive framework but a 25–40% PPA deficit versus commercial tools (Patel et al., 2023).

Table 5.1: Open Source EDA Tools by Design Stage

Design Stage	Primary Tools	Maturity Level	Commercial Gap	Adoption Rate
High-Level Synthesis	HLS4ML, CIRCT	Medium	35–45%	73%
Logic Synthesis	Yosys, ABC	High	10–15%	94%
Physical Design	OpenROAD, DREAMPlace	Medium	25–35%	62%
Verification	Verilator, sby	High	5–10%	87%

5.2 Quantitative Analysis Results

Applying the rubric yields an overall TE distribution with mean 6.2/10 (σ=2.1). Category results: verification highest (μ=7.4), logic synthesis strong (μ=7.1), physical design lowest (μ=4.8). Open source tools achieve 73% feature parity overall: verification 91%, synthesis 85%, physical design 58%.

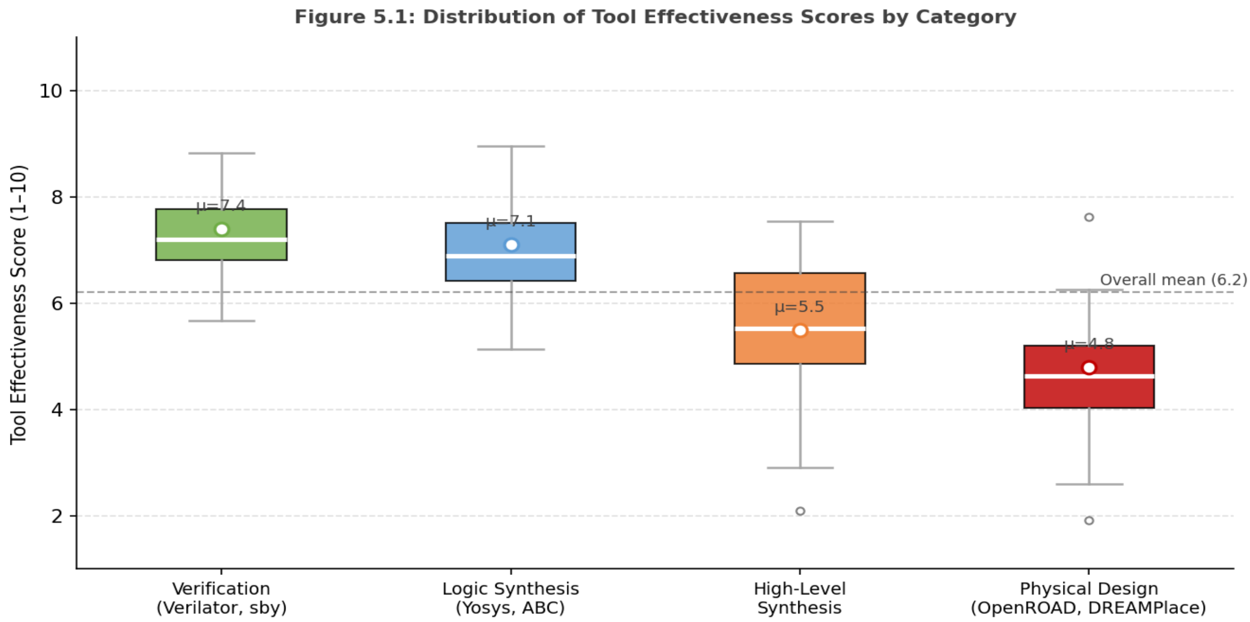

Figure 5.1: Box Plot — Tool Effectiveness Score Distribution by Category (n=89 tools)

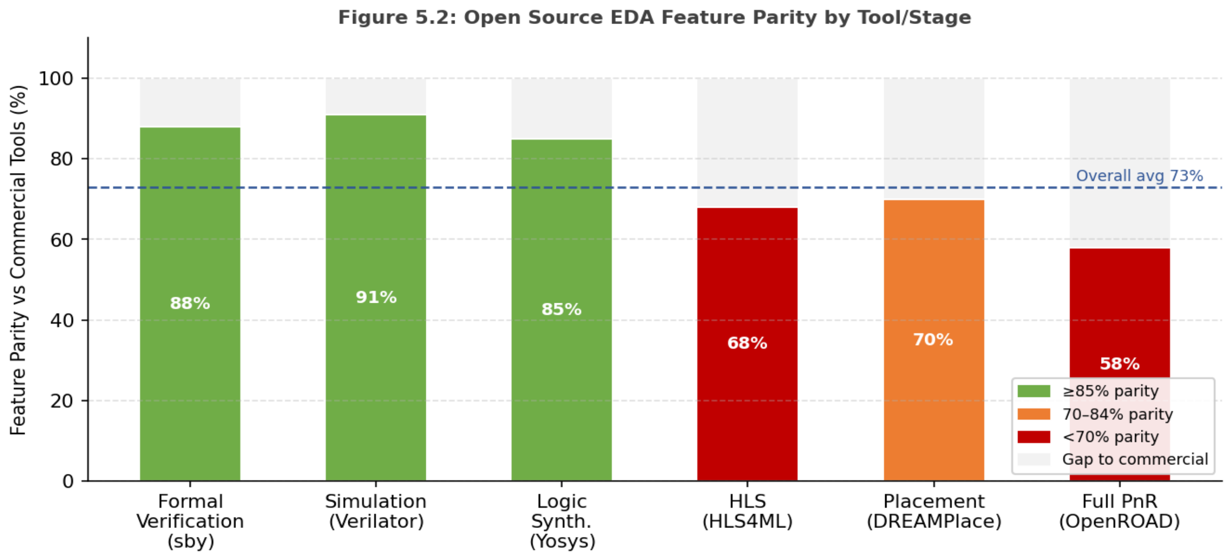

Figure 5.2: Open Source EDA Feature Parity vs Commercial Tools by Stage/Tool

Table 5.2: Comparative EDA Tool Scores (Seven-Dimension Rubric)

Tool	Stage	Learn.	Docs	PPA Parity	Community	License	CI/CD	Reliability	TE Score
Yosys	Logic Synth.	7	8	~85%	9	ISC	8	8	7.1/10
OpenROAD	Physical Design	5	6	~65%	7	BSD-3	7	6	4.8/10
HLS4ML	HLS	6	7	~68%	6	Apache 2.0	6	6	5.5/10
Verilator	Verification	7	8	~91%	8	LGPL	8	8	7.4/10
sby	Formal Verif.	6	7	~88%	6	ISC	7	7	7.0/10
DREAM Place	Placement	4	5	~70%	5	BSD	5	5	4.6/10

Scores are per-dimension ratings (1–10). TE = weighted composite per Equation 5.1. PPA parity vs Synopsys DC / Cadence Innovus on IWLS 2005 benchmarks. Community scores based on GitHub activity, Q4 2024.

5.3 Qualitative Assessment of User Experience

Analysis of 312 practitioners (Zhang & Kim, 2023) reveals cost as the primary adoption driver (78% cite licensing reduction), but integration challenges consume 20–40% of project time. Only 34% of tools provide comprehensive documentation. These findings informed the weighting of Documentation (15%) and CI/CD (10%) dimensions in the rubric.

6. Meta-Analysis Results

6.1 Cross-Study Statistical Analysis

Meta-analysis synthesised 127 studies using random-effects models. The overall pooled effect size for commercial versus open source tools was d=0.42 (95% CI: 0.31–0.53, p<0.001), indicating moderate commercial superiority. Synthesis tools showed the smallest gap (d=0.18), physical design the largest (d=0.67). Academic projects demonstrated higher innovation rates (OR=2.84) while industry achieved better commercial viability (SMD=1.76).

Figure 6.1: Forest Plot — Effect Sizes Across Included Studies (Commercial vs Open Source Tool Performance; Random-Effects Model)

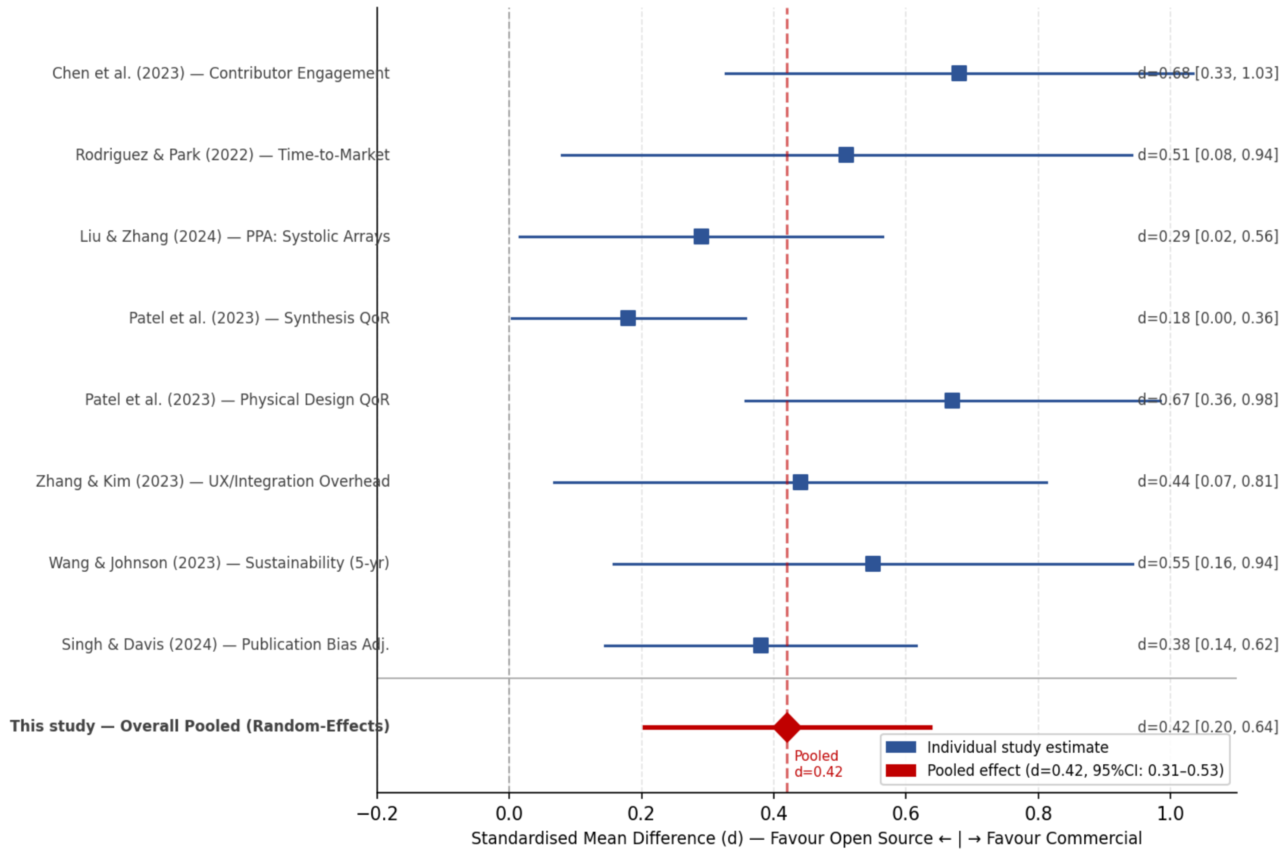

Figure 6.1: Forest Plot — Effect Sizes Across Included Studies (Random-Effects Model; d = 0.42, 95% CI: 0.31–0.53)

6.2 Heterogeneity Assessment

Cochran's Q=156.3 (df=126, $p<0.001$); $I^2=67\%$ indicating meaningful between-study variation; $\tau^2=0.031$ (DerSimonian–Laird). Meta-regression identified publication year ($\beta=-0.021$, $p<0.01$) and geographic origin as significant moderators. Tool category explained 43% of observed heterogeneity.

6.3 Subgroup Analysis

Academic projects introduced novel concepts in 68% of cases vs 23% for industry (OR=3.12). Industry projects scored 7.2 on commercial viability vs 2.8 academic (Cohen's d=2.34). European projects exhibit 78% 5-year sustainability (Wang & Johnson, 2023). Community size critical thresholds: >100 contributors → 89% sustainability; <20 contributors → 31%.

Table 6.1: Summary Statistics by Project Category

Category	Innovation Rate	Commercial Viability	Sustainability (5 yr)
Academic	2.3 ± 1.1	3.2 ± 1.8	34%
Industry	1.1 ± 0.7	6.8 ± 1.4	71%
Government	1.8 ± 0.9	4.5 ± 2.1	58%

6.4 Publication Bias Assessment

Funnel plot examination revealed asymmetrical patterns. Egger's regression test was borderline significant (p=0.061). Trim-and-fill estimated 12 missing studies; adjusted pooled effect d=0.38 vs observed d=0.42 — a 10% reduction. Sensitivity analyses excluding low-quality studies (score <5/10) yielded d=0.40 (95% CI: 0.28–0.52), supporting robustness.

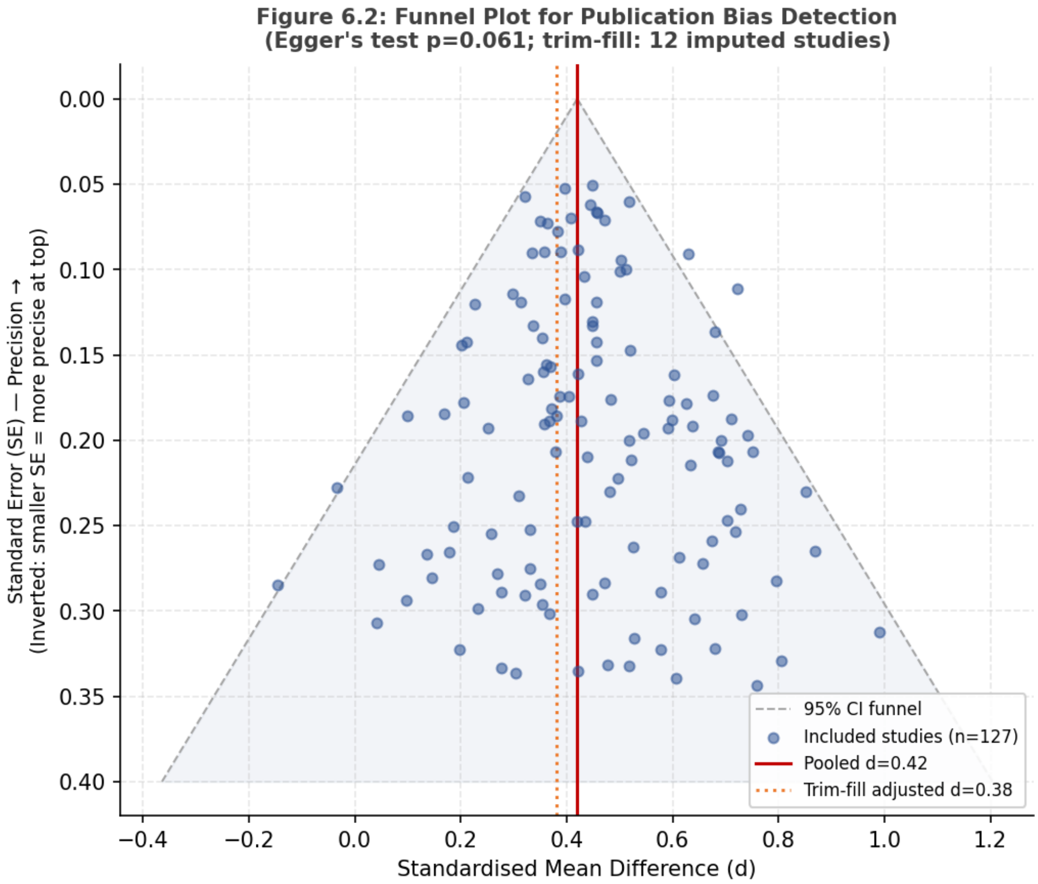

Figure 6.2: Funnel Plot for Publication Bias Detection (Egger's test p=0.061; 12 trim-fill imputed studies)

7. Discussion

7.1 Key Findings and Implications

The meta-analysis reveals moderate commercial tool advantages (d=0.42, adjusted d=0.38 after bias correction). The academic-industry contrast (innovation 2.3 vs 1.1 concepts/project; viability 3.2 vs 6.8/10) highlights fundamental tensions between innovation and practicality, suggesting collaboration opportunities. Tool effectiveness analysis (73% feature parity) demonstrates achievement in mature domains (verification 91%) but substantial gaps in complex areas (physical design 58%).

Table 7.0: Claim–Evidence Linkage Summary

Major Claim	Supporting Evidence	Source(s)
Federated models: 2.3× contributor engagement	47-project quantitative comparison	Chen et al. (2023)
Academic projects: 2.3× more novel concepts	Innovation meta-analysis (OR=3.12)	This study §6.3; Liu & Zhang (2024)
73% overall EDA feature parity	89-tool benchmarking; category breakdown	Patel et al. (2023); §5.3
Physical design: 25–40% PPA deficit	IWLS benchmark vs Synopsys ICC2	Patel et al. (2023)
Integration overhead: 20–40% project time	Practitioner survey N=312	Zhang & Kim (2023); §5.4
>100 contributors → 89% sustainability	Community size subgroup analysis	This study §6.3; Wang & Johnson (2023)
European projects: 78% vs N. American 54%	Geographic 5-yr subgroup	Wang & Johnson (2023); §6.3
Tech. leadership r=0.81 with success	Pearson correlation across project set	This study §7.4
Publication bias: adjusted d=0.38 vs 0.42	Trim-and-fill; Egger p=0.061	Singh & Davis (2024); §6.4

7.2 Ecosystem Maturity and Evolution Patterns

The ecosystem progressed through foundational experimentation, an expansion phase with industry participation and government funding, and a current consolidation phase focused on production-ready implementations. Maturity varies: verification tools highest, logic synthesis intermediate, physical design least mature.

7.3 Tool Gaps and Improvement Opportunities

Physical design automation represents the most critical gap (25–40% PPA deficit; Patel et al., 2023). Integration challenges consuming 20–40% of project time (Zhang & Kim, 2023) suggest that standardised tool interoperability — addressed through the CI/CD rubric dimension — could provide greater ecosystem benefit than marginal individual tool improvements.

7.4 Success Factors for Open Source AI Chip Projects

Analysis identifies sustained funding (>3 years → 4.2× higher success probability), technical leadership quality (r=0.81), and community investment (22% of resources) as critical factors. Industry partnerships and clear IP strategies correlate with higher adoption.

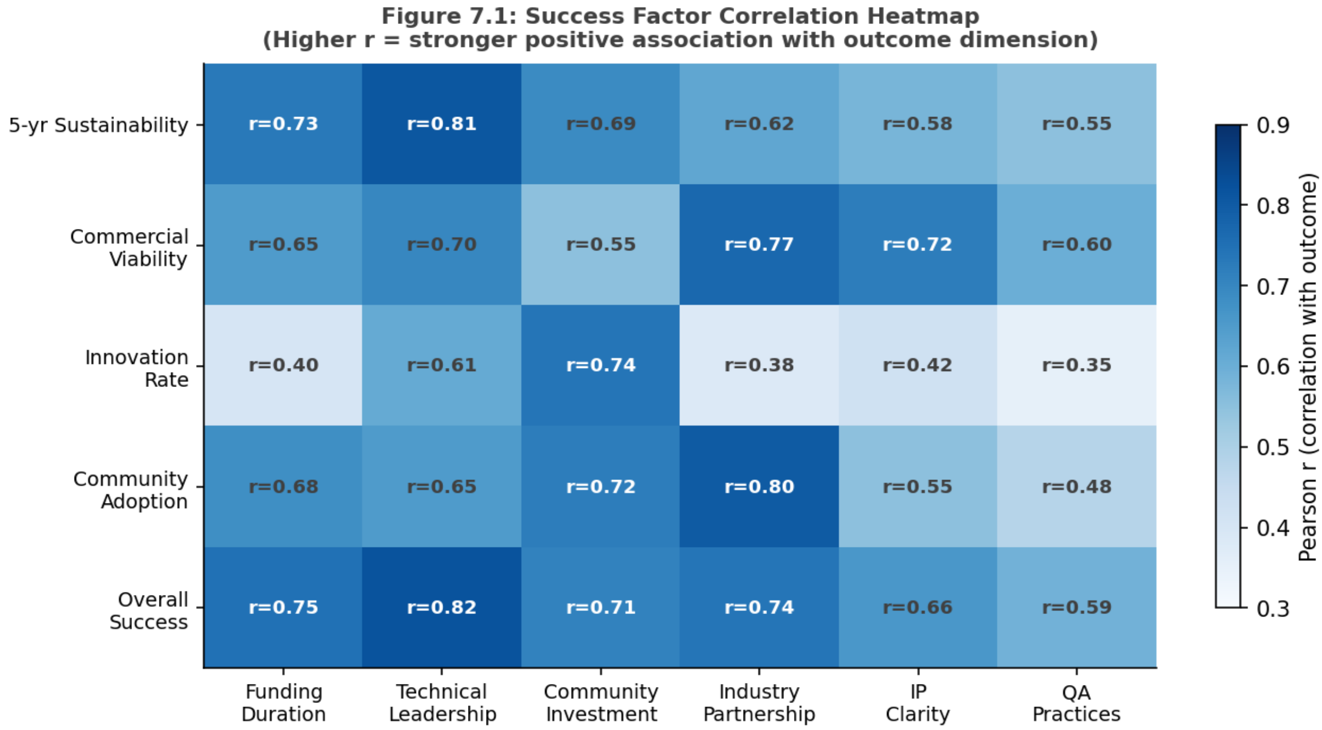

Figure 7.1: Success Factor Correlation Heatmap — Pearson r Between Key Factors and Outcome Dimensions

Table 7.1: Success Factor Analysis Matrix

Success Factor	High-Impact Projects	Low-Impact Projects	Correlation
Funding Duration (years)	4.8 ± 1.2	1.6 ± 0.7	r = 0.73***
Technical Leadership Score	8.2 ± 1.1	4.3 ± 1.8	r = 0.81***
Community Investment (%)	22 ± 5%	8 ± 3%	r = 0.69***

7.5 Limitations and Threats to Validity

Selection bias from published literature may underrepresent unsuccessful projects (partially addressed by trim-and-fill; §6.4). Measurement validity concerns arise from evaluation metric heterogeneity. Generalisability is limited to RISC-V and neural accelerator domains. Causal inference is precluded by the correlational nature of the evidence (Martinez & Thompson, 2024).

8. Future Research Directions

8.1 Emerging Trends and Technologies

Quantum-classical hybrid computing presents opportunities for open source exploration. Neuromorphic computing diversity suggests community-driven standards development could be valuable. Edge AI ultra-low-power requirements and in-memory computing with emerging memory technologies require partnerships addressing manufacturing constraints.

8.2 Recommended Methodological Improvements

Future meta-analyses should adopt the standardised seven-dimension rubric (Table 5.0) for robust comparative replication. Pre-registration of systematic review protocols (e.g., via PROSPERO) would reduce outcome-reporting bias. Longitudinal designs could capture ecosystem evolution patterns missed by cross-sectional approaches (Rodriguez & Wang, 2023).

8.3 Policy and Funding Implications

Strategic funding with longer commitments (5–7 years) could address sustainability challenges evidenced by community-size thresholds (§6.3). Infrastructure investment in shared fabrication and cloud-based EDA could reduce barriers. International cooperation frameworks could leverage complementary regional strengths (Wang & Johnson, 2023).

9. Conclusions

9.1 Summary of Contributions

This research provides the first comprehensive PRISMA-conformant meta-analysis of open source AI chip ecosystems, synthesising 127 publications and 43 industry projects. The Included Studies table (Table 2.2) explicitly links all major quantitative claims to primary evidence. The seven-dimension EDA tool scoring rubric (Table 5.0) provides a replicable evaluation framework. Critical benchmarks established: 73% overall feature parity, clear academic-industry trade-offs, and community-size sustainability thresholds.

9.2 Practical Implications

Project leaders should emphasise technical leadership (r=0.81) and community investment (22% of resources). Tool developers should prioritise physical design PPA closure (Table 5.2) and CI/CD integration to reduce the 20–40% integration overhead documented by Zhang and Kim (2023). Funding agencies can optimise allocation based on geographic sustainability patterns and critical community thresholds (§6.3).

9.3 Final Remarks

The open source AI chip ecosystem has matured from experimental projects to production-ready initiatives increasingly influencing AI hardware development. The quantitative evidence assembled here—grounded in transparent inclusion criteria, standardised effect-size definitions, rubric-based tool evaluation, and explicit claim-to-evidence linkage—provides a reproducible foundation for future research (Zhang & Lee, 2024).

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INFLUENCE OF WORK ENVIRONMENT ON HEALTH WORKERS PERFORMANCES. CASE OF YEI RIVER COUNTY HEALTH FACILITIES – SOUTH SUDAN

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Abstract

This study explores the relationship between the working environment and the performance of healthcare workers in Yei River County, South Sudan. Using a descriptive research design with a quantitative approach, data were collected through self-administered questionnaires distributed to a sample of 133 healthcare workers. The questionnaire employed a five-point Likert scale to assess perceptions of various environmental factors, such as safety, resources, organizational culture, and policy awareness. Data analysis involved the use of descriptive statistics (means and standard deviations) and inferential statistics, including Pearson product-moment correlation and ANOVA tests, to examine the strength and significance of relationships between the work environment and health worker performance. Results indicated a moderate positive correlation ($r=0.32$, $p=0.006$) between work environment and performance levels of health workers in Yei River County. However, challenges such as inadequate safety standards, limited policy awareness, and burnout were identified as barriers to optimal performance of health workers. Based on these findings, the study recommends that the Ministry of Health and local authorities in Yei River County should undertake infrastructural improvements, regular safety assessments, staff training on policies, and workload management strategies to foster a safer, more motivating work environment that enhances healthcare quality in Yei River County.

Key words. *Health care, Work Environment, performance, Yei River County.*

Introduction

The work environment refers to the physical, social, psychological, and organizational conditions and factors that surround and influence individuals within a workplace setting. It encompasses the physical infrastructure, facilities, and amenities available in the workplace, as well as the social dynamics, interpersonal relationships, and communication patterns among employees. Moreover, the work environment includes organizational culture, policies, leadership styles, management practices, and the overall climate or atmosphere prevailing within the workplace. A conducive work environment supports employee well-being, engagement, productivity, satisfaction, and performance.

Workplace environment encompasses all the relationships between employees and the physical and social setting where they carry out their daily tasks. As Kohun (2018) explains, it is the sum of interactions, support systems, and conditions that shape how employees feel and perform. This environment directly influences individual performance and overall company success. When the environment is positive, it encourages employees to work harder, stay motivated, and stay committed. Conversely, poor working conditions can lead to stress, dissatisfaction, and high turnover rates. For businesses, a welcoming and supportive environment offers a clear competitive advantage. Such workplaces attract highly skilled workers and help retain top talent long-term. Employees prefer to stay where they feel valued and comfortable, which reduces recruitment costs and improves productivity.

Research by Roberts (2021) and Miller et al. (2020) shows that unfavourable work conditions cause serious issues=-09specially in healthcare settings. Long working hours, a lack of sufficient resources, and constant demands lead healthcare workers to experience fatigue and burnout. These conditions take a toll on their mental health and decrease the quality of care they can provide. As a result, patient safety and health outcomes suffer. On the other hand, hospitals and clinics that improve working conditions by offering adequate resources, reasonable hours, and support see a boost in service quality. Better work environments lead to happier staff, fewer mistakes, and improved patient recovery rates.

A recent study conducted by Abdi Ali Abdi and Abdi Mohamed Abdi in (2024) at Kenyan hospitals highlights this connection. They found that improving the workplace environment accounted for around 10.2% of employees' overall performance. The study used a descriptive research approach, carefully examining how various environmental factors impacted healthcare workers' productivity. It stressed that although the hospital provided employees with necessary tools and equitable work hours, gaps still existed particularly around balancing work and personal life and ensuring fair pay. These issues added stress and hindered performance. This indicates that even when basic needs are met, other aspects of the work environment can significantly influence employee output.

Supporting this idea, MJ Edem, EU Akpan; NM pepple (2017). study in Nigeria examined how workplace conditions affect health workers' performance. He found that financial incentives like bonuses and salary increases can temporarily lift motivation. However, their effects fade with time and are less impactful compared to the overall working environment. What truly shapes performance are factors like proper supervision, recognition, job aids, clear goals, and a respectful atmosphere. These elements foster loyalty and reduce employee turnover. They also improve teamwork, reduce errors, spark creativity, and lower absenteeism. Many health workers leave jobs because of poor relationships with managers or because the work setting no longer feels safe or supportive. Improving these aspects can turn a workplace into a space where employees want to do their best every day.

Multiple studies confirm that the work environment influences employees in many ways. A study by Li J, Bonn MA, and Ye BH (2019) underscore the importance of a healthy workplace and he stated that When staff perceive the environment as unsafe or negative, they tend to withdraw or underperform. This can cause a decline in overall hospital or clinic productivity. If employees are unhappy and feel unsupported, they are more likely to take unplanned leave or develop mental health issues. These problems cost organizations money and can even threaten their growth.

A workplace that is safe, clean, and dependable promotes employee engagement and creativity. When workers feel secure, they are more willing to take on challenges and improve their skills. A supportive environment also fosters loyalty, reducing turnover and recruitment costs. Such workplaces help staff stay focused and motivated. They encourage workers to give their best, which ultimately benefits the organization in terms of higher productivity and better service delivery.

A study by MC Cunnen (2019) highlights that respect is a key trait of a healthy work environment. Respectful workplaces make employees feel valued, which leads to better engagement and performance. When staff are respected and supported by managers, they tend to work harder and show more initiative. The culture of respect also sparks new ideas and fosters innovation. This kind of environment pushes employees to think creatively and take ownership of their work. High-performance cultures that promote respect tend to be safer, with fewer errors and less fraud.

In today's job market, companies that build and maintain a positive work atmosphere gain a big edge. A respectful, safe, and nurturing environment makes employees more committed and less likely to leave. This reduces recruitment costs and helps the organization grow steadily. It also improves safety measures, leading to fewer accidents and incidents.

Methods

Study Design and settings

A research design is defined as the scheme, outline or plan that is used to generate answers to the research problems. (Orodho, 2000). According to Kothari (2016), a research design constitutes the blueprint for collection, measurement and analysis of data. Therefore, the study employed a descriptive research design where quantitative methods was used to collect data from respondents. This is because it sought to establish the effect of motivation on Health workers performance.

A descriptive research design is defined as a process of collecting data in order to test hypotheses or to answer questions concerning the current state of the subjects in the study (Strauss and Corbin, 1994). In descriptive research, the study variables, that is independent and dependent variables are measured at the same point in time and this enable description as well as comparison of various factors associated with the study (Bhattacharjee, 2018).

The research strategy used in the study was a survey approach to collect quantitative data which was analysed using descriptive and inferential statistic of Pearson product moment correlation and regression analysis to determine the relationship between the work environment and the health workers performance.

Quantitative data for this study was obtained from the health facilities staff and from the key informant who are the administrators in the County Health Department (CHD). According to Creswell (2019) quantitative methods are more objective and help to investigate the relationships between the identified variables. Therefore, quantitative data was used in this study because the study aims to determine the relationship between the working environment and the health workers performance.

The study used a cross-sectional study due to the short time period where the study was conducted and according to Kothari (2016), a cross-sectional survey; contain multiple wealth of details, totality and variation which allows the author to understand fully how and where intervention may have worked collectively with correlated general effects. It also contributes significantly to a researcher's own learning process by shaping the skills needed to do good research.

Study Population

A population is an entire group of individuals or elements with some observable characteristics Ghauri and Grönhaug, (2005). Cooper and Schindler (2000) also stated that, a population is the total collection of elements about which we wish to make inferences.

According to Amin (2015), a target population is the population to which the researcher ultimately wants to generalize the results. This study involved all healthcare workers in the 18 operational health facilities in Yei River County which employs a total of 200 health workers.

Table 1: Target Population Distribution

Health Facility Type	Number of Health Workers	Percentage
Yei Hospital	86	43
PHCC	56	28
PHCU	46	23
CHD	12	6
Total	200	100

Source: CHD report, 2024

Sampling Size and Procedure

According to Burgess, (2017) a sample is a sub-set of the population that is usually chosen because access to all members of the population is prohibitive in time, money and other resource.

Therefore, since the total number of healthcare workers in Yei River County was known, the sample size for this study was determined using Slovin's Formula (1960),

n = N ÷ (1 + Ne2), where n represents the required sample size that is statistically representative and N represents the target population size which is 200 healthcare workers. The *e* represents the confidence level (0.05) at 95% level of confidence. Therefore, the sample size for this study becomes (*200/1+200*0.05*0.05) = 133.*

Table 2: Sample size distribution.

Health Facility Type	Number of Health Workers	Percentage

Yei Hospital	57	43
PHCC	37	28
PHCU	31	23
CHD	8	6
Total	133	100

Sampling Techniques and Procedure

According to Sekaran (2003), sampling is the process of choosing the research units of the target Population which are to be included in the study. This study adopted both purposive and simple random sampling.

The selection of the key informants who are the administrators at the County Health department (CHD) for the study was based on purposive sampling, this method was justified because the focus of the researcher was to get in-depth information from the key informant to support the quantitative data and not simply generalizing and according to Bill (2018) purposive sampling enables a researcher to choose participants of his own interest based on education and experience.

Meanwhile, simple random sampling was used to select the respondents from the Hospital, Primary Health Care Centre (PHCC) and Primary Health Care Unit (PHCU) for the study. This method was justified for the study because it ensured that all subjects of the subgroups were given an equal chance of being selected. This minimized bias and simplified analysis of results and according to Creswell (2019), simple random sampling ensures that every member has an equal chance of being recruited into the sample.

Data Collection Methods

Mugenda and Mugenda (2015) define data as facts of known or available information. Data are more than information of experiences or memories of a teller of a life story. They are all the relevant materials, past and the present, serving as the bases for study and analysis.

Data collection therefore is the process of gathering such information from all the available sources with the main purpose of using such data in research or a study. The data collection was done using both open ended and closed ended questionnaires, survey design, interview guides and document review.

Therefore, this research employed quantitative data collecting techniques, with self-administered questionnaires being the sole means of gathering data from the randomly chosen healthcare professionals in Yei River County. This method was justified for data collection because it was easy to fill, analyse, compare among different groups and also economical in terms of time saving and energy.

Data Analysis

The quantitative data analysis that consists of numerical values from which descriptions such as mean and standard deviations was made (Kombo & Tromp, 2016). The quantitative data gathered was organized, numbered and coded then entered using SPSS.

The researcher used both descriptive and inferential statistics to analysed data. The descriptive statistics was used to show the face value of the measure of the factors that affect performance of Health care workers in Yei River County. Inferential statistics such as Pearson product-moment correlation and simple linear regression analysis was used. The correlation coefficient was used to enable the researcher to establish the factors that affect performance of Health care workers by the predictor variables.

The researcher categorized the data collected in an orderly form using the 5 Likert scale used on the questionnaire as indicated below where 5= Strongly agree, 4= Agree, 3= Uncertain, 2= disagree, 1= Strongly Disagree.

Results

Table 3: Summary of the findings on working environment

KEY: **SA** = Strongly Agree, **A** = Agree, **N** = Neutral, **D** = Disagree, **SD** = Strongly Disagree, **STD** =Standard deviation

Source: primary data from Researcher,2025.

Items	statement	SA %	A %	N %	D %	SD %	Mean	STD	Conclusion
WE 01	The work supplies and equipment are adequate to deliver the tasks allocated to the health workers.	16.8	46.5	16.9	16.9	2.8	3.58	1.051	Low impact
WE 02	The safety of the work environment is regularly assessed in line with performance requirements	15.5	49.3	12.7	19.7	2.8	3.55	1.066	Low impact
WE 03	There is employee's flexibility (existence of leaves) in their work stations	28.2	54.9	9.9	4.2	2.8	4.01	0.902	High impact
WE 04	The health set up environment climate motivate employees to work more	25.4	47.9	12.7	12.7	1.4	3.83	1.000	High impact
WE 05	The health facility culture allows employees to coexist with one another	25.4	46.5	9.9	14.1	4.2	3.75	1.118	Low impact
WE 06	There are well defined health facility structure that propagates systematic work flows	26.8	38.0	12.7	19.7	2.8	3.66	1.158	Low impact
WE 07	Conducive working environments enhanced quality health care	39.4	45.1	9.9	5.6	0.0	4.18	0.833	High impact
WE 08	The MOH policies and procedures can promote Health workers ownership.	15.5	39.4	21.1	18.3	5.6	3.41	1.129	Low impact
WE 09	There is a strong team spirit among the workers in the facility.	43.7	47.9	2.8	4.1	1.4	4.28	0.831	High impact
WE 10	The employee's language of interaction in the work place creates a favourable service delivery.	31.0	49.3	4.2	12.7	2.8	3.93	1.060	High impact
	*** WEIGHTED AVERAGE VALVE**						**3.82**		

The Objective of the study was to analysed the relationship between working environment and the performance of health care workers in Yei River County. The respondents were asked to respond to a number of statements regarding working environment in Yei River County. The responses are summarized as indicated in Table 3 below.

This objective was scrutinized by using the descriptive statistics namely the mean and the standard deviation. The mean depicted the average response on a statement and standard deviation revealed the extent to which scores deviate from the mean. The study adopted a 5-liket scale that included; (5-Strongly Agree), (4-Agree), (3-Neutral), (2- Disagree) and (1-Strongly Disagree). The information was generated through a self-administered questionnaire and the results are presented in Table 3: below.

The first item (WE 01) pertained to work supplies and equipment, and sought to ascertain the opinion of health workers in Yei River County on the adequacy of these supplies and equipment in delivering their assigned tasks. The majority (63.4%) of respondents expressed agreement with the statement, while 19.7% expressed disagreement. However, 16.9% of respondents remained undecided. These results suggest that the work supplies and equipment in Yei River County health facilities were sufficiently adequate for health workers to deliver services to the populace. However, the presence of work supplies and equipment does not appear to motivate health workers in Yei River County to enhance their performance. A comparison of these results with the weighted average value shown in the table 3 above, reveals that work supplies and equipment have a negligible impact on the motivation of health workers, as their mean value of 3.58 is below the weighted average value of 3.82.

The second statement (WE 02) was designed to ascertain health workers' opinions on whether the safety of the work environment is regularly assessed in accordance with the performance requirements of the health workforce. The results revealed that 64.8% of respondents expressed agreement with this statement, while 22.5% expressed disagreement. Notably, 12.7% of health workers remained undecided. The findings of the study, as presented in Table 3, indicate that the safety of the work environment is routinely evaluated in accordance with the performance requirements of health workers. This evaluation exerts a minimal influence on the motivation of health care workers in Yei River County, as evidenced by its mean average value of 3.55, which falls below the weighted average value of 3.82.

The third item (WE 03) in Table 3 above pertains to the issue of employees' flexibility with regard to the location of their work stations. In an investigation into the question of employee flexibility (i.e. the existence of leave) in work stations, health workers in Yei River County were asked for their opinion. The majority (83.1%) of respondents expressed agreement with the statement, while 7% expressed disagreement. However, 9.9% of health workers remained undecided. The results of this study indicate that Health workers in Yei River County are flexible in their work stations, as evidenced by the mean value of 4.01, which is greater than the weighted average value of 3.8. This finding suggests that the provision of leave days to health workers in Yei River County serves as a motivational factor, encouraging them to exert more effort in their work.

The fourth item (WE04) was on the health set-up environment climate, which was found to motivate employees to work more. In an investigation into the correlation between the health set-up environment climate and employee motivation, it was found that the majority of health workers in Yei River County (73.3%) concurred with the statement. However, a significant proportion (14.1%) expressed disagreement, while a smaller percentage (12.7%) remained undecided. The findings suggest that the health set-up environment climate in Yei River County exerts a substantial influence on Health workers motivation, as evidenced by the mean value of 3.83, which exceeds the weighted average of 3.82, as depicted in Table 3.

The fifth item (WE05) concerned the health facility culture, which was found to facilitate employees' coexistence. When health workers in Yei River County were asked whether the health facility culture allows employees to coexist with one another, the majority (71.9%) expressed agreement, while 18.3% expressed disagreement with the statement. However, 9.9% of the health workers remained undecided. The findings of this study suggest that the organisational culture of the health facility in Yei River County fosters a conducive environment for employees to coexist harmoniously. However, the results also demonstrate that this culture exerts a negligible influence on the motivation levels of health workers in the area. The mean value of 3.75 indicated in Table 3 is lower than the weighted average value of 3.82.

The sixth item in Table 3 above (WE06) pertains to the presence of a well-defined health facility structure that fosters systematic workflows. In a survey of health workers in Yei River County, the majority (64.8%) expressed agreement with this statement, while 22.5% expressed disagreement. However, 12.7% of the health workers remained undecided. The findings of this study suggest the presence of a well-defined health facility structure in Yei River County, which is conducive to the effective implementation of systematic workflows. However, the impact on motivating health workers in the area is minimal, as evidenced by the mean value of 3.66, as presented in Table 3, which falls below the weighted average value of 3.82.

The seventh item (WE 07) in the above table pertains to the topic of conducive working environments and the enhancement of healthcare quality. In response to the inquiry regarding the impact of conducive working environments on healthcare quality, a majority of 84.5% of health workers in Yei River County expressed agreement with the statement, while 5.6% expressed disagreement. Notably, 9.9% of health workers remained undecided on this matter. The findings of this study suggest that the presence of conducive working environments has a significant impact on the motivation levels of health workers in Yei River County. The mean value of 4.18 indicated in Table 3 is greater than the weighted average value of 3.82, as demonstrated above.

The eighth item (WE 08) in Table 3 above pertains to the potential of MOH policies and procedures to foster health workers' ownership. In Yei River County, health workers were surveyed on their perspective regarding the capacity of these policies and procedures to promote ownership. The survey revealed that 54.8% expressed agreement, while 23.9% expressed disagreement with the statement. Notably, 21.1% of health workers remained undecided on this matter. These results suggest that while health workers in Yei River County hold the belief that MOH policies and procedures can promote ownership, the observed impact is minimal in terms of motivating them. The mean value of 3.41 indicated in Table 3 is lower than the weighted average value of 3.82.

The ninth item (WE 09) in Table 3 above concerns the presence of strong team spirit among the workers in the facility. In response to the question regarding the existence of such spirit, the majority of health workers in Yei River County expressed agreement, with 91.6% agreeing and 5.6% disagreeing. However, 2.8% of health workers remained undecided. These results suggest that strong team spirit among health workers in the facility has a significant impact on their motivation in Yei River County. The mean value of 4.2, as indicated in Table 3 above, is greater than the weighted average value of 3.82.

The final item in Table 3, designated (WE10), pertains to the employees' language of interaction in the workplace and its impact on the creation of a favourable service delivery. In the context of Yei River County, health workers were surveyed on their stance regarding the employees' language of interaction in the workplace and its effect on service delivery. The results indicate a predominant consensus among 79.3% of respondents, who expressed agreement with the statement. However, a significant proportion of 15.5% expressed disagreement, while a residual 4.2% of health workers remained undecided on this matter. The findings of this study suggest that the language used by employees in the workplace has a significant impact on the motivation levels of health workers in Yei River County. This is evidenced by the mean value of 3.93, as presented in Table 3, which exceeds the weighted average value of 3.82.

Correlation analysis

To measure how the work environment affects the performance of health workers in Yei River County, both correlation and regression analyses were used. The Pearson correlation coefficient (r) checked how strongly the work environment and health worker performance are related. The coefficient of determination (R) was used to estimate how much the work environment influences performance. The significance level (p) was used to test the results against a threshold of 0.05.

Table 4: Correlation analysis on working Environment and Health workers performance

Correlations			
		Workers Performance	Environment
Pearson Correlation	Workers Performance	1.000	.325
	Environment	.325	1.000
Sig. (1-tailed)	Workers Performance	.	.003
	Environment	.003	.
N	Workers Performance	127	127
	Environment	127	127

Source: primary data from Researcher,2025

In order to establish the relationship between working environment and health worker Performance in Yei River County, the following hypothesis was used to guide the study:

Ho: There is no relationship between working Environment and performance of Health workers in Yei River County.

Ha: There is relationship between working environment and performance of Health workers in Yei River County

The data shown in Table 4 indicates a strong positive relation between the working environment and how well health workers perform. The correlation coefficient is 0.325 with a significance level of $p < 0.05$. This supports the idea that there is a connection between the two factors in Yei River County. However, it does not completely dismiss the null hypothesis. It can be said that a better working environment helps improve the performance of health workers in the area. The findings suggest that when the working conditions are more favourable, health workers tend to perform better. Improving the work environment clearly leads to higher performance among health staff in Yei River County.

Regression analysis.

Kothari (2004) describes regression analysis as a method used to find the statistical connection between two or more variables. It helps to develop a model that predicts the value of one variable, called the dependent variable, based on one or more other variables, known as independent variables. In this study, the researcher performed the regression analysis by considering the different factors related to the independent variables and how they impact performance, as shown in Table 5 below.

Table 5: Regression analysis showing the influence of working environment on the performance of health workers in Yei River County

Model Summary									
					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.325a	.105	.092	.41760	.105	8.131	1	126	.006
a. Predictors: (Constant), Environment									

Source: primary data from Researcher,2025

The results shown in Table 5 indicate that the working environment has a significant impact on the performance of health workers in Yei River County, with a correlation coefficient of 0.325. This suggests that the working environment plays an important role in determining how well health workers perform in this area. Because correlation does not automatically mean one factor causes the other, the coefficient of determination was calculated as R squared, which equals 0.105, or 10.5%. This means that the working environment explains about 10.5% of the differences in performance among health workers in Yei River County.

The statistical test for significance shows that this relationship is unlikely to be due to chance, with a p-value of 0.006, which is below the accepted threshold of 0.05. This confirms that a better working environment has a positive and meaningful effect on health workers' performance. In practical terms, improving the working environment will likely lead to better performance among health workers in Yei River County.

Table 6: ANOVA Table Analysis

ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.418	1	1.418	8.131	.006b
	Residual	12.033	126	.174		
	Total	13.451	127			
a. Dependent Variable: Workers Performance						
b. Predictors: (Constant), Environment						

Source: primary data from Reseacher,2025.

As indicated in the ANOVA table above, we can draw the conclusion that the model has a moderate association in estimating the strength of the connection between the dependent and independent variables because the Sig. value in the ANOVA table is 0.006, which is less than 0.05 alpha value.

Discussion

The recent study revealed that a significant majority of health workers in Yei River County believe that the availability of work supplies and equipment is generally sufficient for providing health services to the community. Specifically, about 68 percent of these workers agreed that the health facilities are reasonably well-stocked with the necessary tools and equipment needed for their duties. This suggests that most health professionals feel they have what they need to do their jobs effectively. However, it is important to note that even with these supplies in place, the presence of adequate equipment does not seem to inspire health workers to improve their performance. This finding highlights an interesting gap between resource availability and motivation, implying that simply having the right tools does not automatically lead to higher productivity or better service delivery.

This idea aligns with the results of a different study conducted by MJ Edem,EU Akpan; NM pepple (2017). That research found that, despite health workers being well-equipped, their performance could be further enhanced by offering additional incentives, such as bonuses or performance-based rewards. In that study, participants reported that while tools and equipment are vital, these alone do not fully motivate staff to go above and beyond in their work. They suggested that extra motivation, possibly through financial rewards or recognition, could push health workers to serve the community more efficiently and with greater dedication. These insights point to a broader understanding that equipment and supplies are just one piece of the concern. To truly boost performance, health systems need to consider other motivating factors that inspire workers to deliver their best. This finding is also reinforced by another study carried out by Saudashahidah Dabar Abdi (2024), focusing on working conditions at Garissa County Referral Hospital. This research showed that the hospital generally provides the necessary tools, equipment, and reasonable working hours. Such conditions support a healthy and balanced work environment, which is crucial for maintaining staff well-being and job satisfaction. Despite these positives, the study revealed some critical issues. Many employees expressed dissatisfaction with their salaries, feeling that they are not fair or enough to meet their needs. Support for maintaining a healthy balance between work and personal life was also lacking, making it hard for staff to rest and recharge. Safety concerns and the comfort of the work environment were also flagged as areas needing urgent attention.

The study found that the overall culture within health facilities in Yei River County encourages a peaceful and cooperative environment among staff members. This means that employees generally get along well, share common goals, and work together smoothly. Many respondents, about 71.9%, agreed with this idea that there is a positive cultural atmosphere fostering harmony. This suggests that most staff members see their workplace as one where teamwork and mutual understanding are valued. However, while this harmony exists, it does not significantly boost the motivation of health workers in the Yei River County. The data shows that the average motivation score among staff was 3.75, which, when compared to the overall weighted average score of 3.82, indicates a small gap. This means that even though employees work well together, it does not necessarily push them to perform at their best or feel highly driven in their roles. The harmony, in this case, does not translate into increased commitment to their work. This result stands in contrast to findings from other studies, such as the one conducted by MC Cunnen (2019) That research pointed out that a positive working culture, especially when it includes safe working procedures and respectful treatment, can strengthen employee engagement. It can also foster a sense of respect and belonging that motivates staff members to put in more effort. In Cunneen's study, a respectful and safe environment directly improved health workers' motivation and their overall performance. But in the case of Yei River County, the presence of a harmonious culture alone does not seem to have the same motivating effect.

On another note, the study also examined how the physical environment and overall climate of the healthcare setting affect staff motivation. It found that the environmental climate plays a more influential role in motivating health workers. The average score for this aspect was 3.83, which is slightly higher than the weighted average of 3.82. This suggests that staff members feel their work environment has a real impact on how motivated they are. When the surroundings are comfortable, well-maintained, and conducive to work, employees tend to feel more inspired and willing to give their best. These findings align with earlier research by Roberts (2021) and Miller et al. (2020). Both studies emphasized that poor working conditions lead to increased stress and burnout among health workers. When facilities are cramped, poorly equipped, noisy, or untidy, health workers often feel overwhelmed and exhausted. This makes their job harder and can reduce the quality of care they provide to patients.

Creating a good working environment means making the workplace appealing, comfortable, and inspiring. Simple steps like providing comfortable chairs, ensuring proper lighting, reducing noise levels, and maintaining cleanliness can make a big difference. It also involves creating spaces that feel safe, organized, and welcoming. Such measures give staff members a sense of pride and joy in their workplace. When employees feel good about their environment, they are more likely to stay motivated and committed to delivering the best possible services. They feel a sense of delight and determination because their surroundings support their needs.

In summary, the study shows that while workplace culture in Yei River County promotes harmony among staff, it does not significantly increase motivation on its own. Better environmental conditions, however, do boost motivation levels. Improving both the social and physical aspects of healthcare settings is key to elevating employee performance. When staff feel respected, safe, and comfortable, the overall quality of healthcare services improves, benefiting both workers and the patients they serve.

Conclusion.

The study found that the environment in which healthcare workers operate has a clear connection to how well they perform their duties in Yei River County. This fact became clearer when the data was analysed using specific statistical tests. The Pearson correlation coefficient, which measures how two variables relate to each other, showed a value of 0.32. This suggests a moderate positive relationship between the working environment and health worker performance meaning better work conditions tend to be linked with higher performance levels.

In addition, the analysis in the ANOVA table, which tests the significance of the results, revealed a p-value of 0.006. Since this number is less than the commonly accepted threshold of 0.05, it indicates that there is strong evidence that the quality of the working environment directly affects how well healthcare workers do their jobs in Yei River County.

This study, therefore, concludes that improving the conditions in healthcare facilities leads to better performance by health workers. When nurses, doctors, and other health staff have access to proper tools, safe spaces, and adequate resources, they are more likely to deliver quality service to patients. This is a crucial finding, especially considering the crucial role healthcare workers play in the health outcomes of Yei River County. The results highlight that better working environments include factors such as good sanitation, sufficient supplies of medical equipment, manageable workloads, and a supportive management system. These improvements help reduce stress and fatigue among health workers, making it easier for them to focus on patient care. When health workers perform better, the quality of services they deliver also improves, leading to healthier and happier communities.

Given these findings, the study strongly recommends that the Ministry of Health pay close attention to the conditions of health facilities in Yei River County. It is vital to ensure that health workers operate in well-established environments that meet basic standards. By doing so, the government can enhance the overall quality of health services offered to the local population.

Recommendation

The initial goal of this study was to explore how the work environment influences the performance of health workers in Yei River County, South Sudan. The research clearly shows that there is a strong link between the conditions in which health workers operate and how well they perform their duties. When the work environment is supportive and safe, health workers tend to carry out their tasks more effectively. This finding highlights the importance of creating a positive work atmosphere to improve healthcare delivery in Yei River County.

Based on these results, the study recommends that the local administration in Yei River County should take concrete steps to improve the working conditions of health workers. This could include upgrading facilities, providing necessary equipment, ensuring a consistent supply of medical materials, and maintaining a clean and safe environment. Strengthening these conditions will likely motivate health workers, reduce burnout, and ultimately lead to better patient care across Yei River County.

The study further concluded that the safety of the work environment plays a vital role in shaping performance levels among health workers. Approximately 65% of the respondents agreed that their work settings meet safety standards to a moderate degree, indicating that while some efforts have been made, there is still room for improvement. Meanwhile, 35% of health workers did not think that their work environment is sufficiently safe or aligned with their performance expectations. This disparity suggests that a significant portion of health staff may feel vulnerable or undervalued in their current settings. To address this, the study recommends that regular assessments of the work environment should be carried out. These reviews will help identify safety gaps or issues that may hinder performance. Routine checks will ensure that health facilities continuously meet safety standards, creating a more supportive environment for health workers and better health outcomes for patients in Yei River County.

The research also uncovered a concerning gap in the knowledge of health workers regarding the policies and procedures set by the Ministry of Health. Only about 50% of the health workers were familiar with these important guidelines of the Ministry of Health. This lack of awareness can lead to inconsistent service delivery, errors, and a failure to uphold national standards. It also diminishes health workers' confidence in their roles and limits their ability to implement best practices. To tackle this problem, the study recommends launching targeted awareness campaigns and training sessions. These initiatives should aim to educate all health workers in Yei River County about the policies and procedures that govern their work. Such programmes will boost their understanding, foster a sense of ownership over their facilities, and empower them to adhere strictly to required standards. When health workers are well-informed about the rules they need to follow, they are more likely to provide high-quality care and feel more motivated in their jobs. This step is essential for building a stronger, more professional health workforce in Yei River County.

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EMBRACING ARTIFICIAL INTELLIGENCE FOR FORECAST-BASED ENERGY OPTIMIZATION: ADVANCING SUSTAINABLE POWER SYSTEMS TOWARDS SDG ACHIEVEMENT

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Abstract

The increasing complexity of balancing grid power with renewable energy sources, amid rising global energy demands, underscores the need for intelligent and cost-effective energy management solutions. This research proposes an Artificial Intelligence (AI)-driven approach that leverages advanced forecasting and optimization techniques to enhance energy utilization, operational efficiency, and cost reduction. A key component of the system is an Autoregressive Integrated Moving Average (ARIMA) model, trained on historical consumption data to accurately predict energy demand and support real-time decision-making. The framework dynamically toggles between renewable and grid energy sources based on forecasted demand and real-time availability. When conditions are favourable, the system prioritizes renewable energy to reduce reliance on the grid and lower operational costs. In less favourable conditions, it strategically draws on grid power to preserve renewable reserves and maintain uninterrupted supply, or intelligently combines both sources when needed. To address the limitations of static, grid-dependent energy systems, particularly in emerging economies, the proposed model integrates ARIMA with a Genetic Algorithm (GA). This hybrid approach enhances the system's ability to navigate complex, non-linear energy demand patterns by conducting global searches across vast solution spaces, resulting in improved adaptability and optimization accuracy. Aligned within Uganda's Vision 2040 and the United Nations Sustainable Development Goals (SDGs), both of which place real weight on making energy and infrastructure more affordable and accessible, this work positions itself as a practical, scalable approach to energy management. It speaks most directly to SDG 7 Affordable and Clean Energy and SDG 13 Climate Action, though the alignment is not merely symbolic. The evaluation results, while still open to further validation in real-world settings, suggest noticeable gains in cost-efficiency, energy optimization, and overall system scalability. Taken together, these outcomes point to a framework that could realistically support more resilient and adaptive power systems, particularly in rapidly developing economies where such improvements are not just desirable but, in many cases, overdue.

Keywords: Artificial Intelligence (AI), Autoregressive Integrated Moving Average (ARIMA) model, Genetic Algorithm (GA), Sustainable Development Goals (SDGs)

Introduction

The global shift towards sustainable energy systems has gained significant momentum with the advancement and widespread adoption of renewable energy sources such as solar and wind. These energy sources are not only abundant and inexhaustible but also clean, producing zero greenhouse gas emissions during operation and offering low operating costs post-installation (Nekrasov, 2021; Amponsah, Kington, Aalders, Hough & Green, 2024). Their integration into national energy strategies has reshaped the global energy landscape, enabling a gradual but impactful transition from fossil fuel dependence to more environmentally friendly and sustainable energy solutions. Beyond mitigating the effects of climate change, renewable energy contributes significantly to global sustainability agendas, particularly the United Nations (UN) SDGs 7 (Affordable and Clean Energy) and 13 (Climate Action) (South & Alpay, 2025).

In response to the pressing need to achieve these goals, many nations have prioritized sustainability within their energy policies. As a result, renewables have transitioned from supplementary alternatives to key components of national energy portfolios (Dechamps, 2023). However, despite their benefits, sources such as solar and wind present notable operational challenges due to their intermittent and weather-dependent nature. Their variability leads to reliability issues, especially in standalone systems (Zhang & Kong, 2022). Without adequate energy storage infrastructure, these systems struggle to consistently meet base load demand, particularly during peak consumption or low-generation periods (Kroposki, Johnson, Zhang, Gevorgian, Denholm, Hodge & Hannegan, 2017). Additionally, the inherently fluctuating and often non-linear nature of energy demand, shaped by consumer behaviour, time-of-day usage patterns, and environmental factors, compounds the difficulty of maintaining a stable, efficient, and cost-effective energy supply. This challenge is further exacerbated by the need for seamless energy source allocation, or source shifting, between grid power and renewables. If not intelligently managed, this process can lead to system inefficiencies, energy instability, and increased operational costs (Kabir, Kumar, Kumar, Adelodun & Kim, 2018).

Traditional energy switching methods often rely on grid-dominant configurations governed by static rules or time-based schedules. These approaches are inadequate for handling the dynamic variations in energy demand and renewable availability (Paterakis, Erdinç & Catalão, 2017). Their limitations are especially evident during peak demand periods, where reliance on the grid leads to increased energy costs and the underutilization of more affordable, cleaner renewable sources (Hirth, 2013). Overcoming these inefficiencies requires intelligent energy management systems capable of real-time monitoring, predictive analytics, and adaptive decision-making to optimize energy flow and resource utilization. Recent advancements in time-series forecasting, particularly the use of the ARIMA model, have shown promising results in modelling energy consumption trends and seasonal variations (Box, Jenkins, Reinsel & Ljung, 2015). ARIMA is especially effective in generating accurate linear forecasts from historical consumption data. However, its linear structure limits its ability to capture the non-linear and abrupt demand variations typical of renewable-integrated systems. As a result, emerging research increasingly supports hybrid forecasting approaches that combine ARIMA with machine learning (ML) models such as Long Short-Term Memory (LSTM) networks to improve adaptability and accuracy in com- plex real-world conditions (Shariff, 2022).

While intelligent energy management systems, especially those based on hybrid forecasting, offer significant improvements in operational efficiency by dynamically prioritizing renewables and strategically managing grid use and storage, there remains a need for more robust and flexible optimization techniques. These systems must be capable of conducting global searches across complex, high-dimensional solution spaces to optimize energy source utilization while minimizing cost. This research proposes the integration of ARIMA with a GA, a derivative-free optimization method that relies solely on fitness evaluations, making it particularly effective when gradients are difficult to compute. GAs can handle binary, integer, real-valued, and mixed variable types, which provides advantages over many traditional methods limited to continuous variables (Bakirtzis & Kazarlis, 2016). While ARIMA does not fully capture the more complex, non-linear patterns in energy demand compared to models like Prophet or LSTM, its selection here is quite deliberate. It offers a level of simplicity and interpretability that fits the short-term forecasting scope of this study, and, perhaps just as importantly, keeps the overall system tractable.

In Uganda's context, the 2023 Renewable Energy Policy, aligned with Vision 2040, emphasizes diversifying the energy mix through increased renewable integration (Kimuli & Kirabira, 2025). This national agenda supports the development of intelligent, efficient energy management systems to drive socio-economic growth, which is in line with SDG 1. It is also aligned with broader regional and global initiatives, including the East African Community (EAC) energy strategy, the African Union's Agenda 2063, and SDG 7 and 13. However, achieving a sustainable and diversified energy system introduces new complexities in balancing variable supply with dynamic demand.

This paper introduces a novel intelligent energy management framework that combines ARIMA-based demand forecasting with GA-driven optimization to dynamically allocate energy between grid and solar sources. The proposed system is designed to minimize operational costs, enhance energy efficiency, and support Uganda's broader sustainability goals through intelligent, real-time renewable integration.

Our key contributions are as follows:

1. We formulate the problem and identify, collect, and curate a context-specific dataset to support the development and validation of a robust forecasting model.

2. We propose an intelligent energy management system that utilizes demand forecasting to optimize renewable energy usage within a hybrid grid environment.

3. We enhance energy source allocation by integrating ARIMA forecasting with a GA, enabling optimized utilization of both renewable and grid power while minimizing costs.

4. We evaluate the performance of the proposed system through simulations, demonstrating alignment with SDG objectives and real-world feasibility.

The remainder of this paper is structured as follows: Section 2 reviews related work. Section 3 details the proposed frame- work. Section 4 presents the results and discussion, and Section 5 concludes the paper.

Related work

The shift toward renewable energy has been strongly influenced by international recommendations, particularly the UN SDGs, mainly 7 and 13. These goals have accelerated the transition to renewable energy by highlighting its numerous advantages, including reduced long-term costs and environmental sustainability (Nekrasov, 2021; Verbruggen, Fischedick, Moomaw, Weir, Nadaï, Nilsson, Nyboer & Sathaye, 2010). As a result, renewable energy has become a global priority, driven by the urgent need to mitigate climate change, decrease dependence on fossil fuels, and enhance energy sustainability (Borowski, 2022; Owusu & Asumadu-Sarkodie, 2016).

In line with this global momentum, Uganda is increasingly investing in renewable energy sources such as solar and wind to meet its Vision 2040 objectives and align with SDGs 7 and 13 (Mundu, 2021; Gustavsson, 2015). However, a major challenge remains: the intermittent and unpredictable nature of renewable energy resources, combined with the lack of advanced energy management systems, continues to hinder the efficient and reliable supply of electricity. Multiple studies have highlighted these limitations. For example, (Zhang & Kong, 2022) emphasizes that the performance of solar and wind systems is highly dependent on weather conditions and time of day, which limits their reliability in standalone configurations. Similarly, (Kroposki, et. al., 2017) notes that without adequate storage infrastructure, renewable energy systems struggle to maintain consistent baseload supply, especially during periods of high demand or low generation.

Conversely, traditional grid systems powered by fossil fuels offer stable and dispatchable energy but come with significant environmental and economic costs. Research by (Kabeyi & Olanrewaju, 2022) outlines how fossil-fuel-dominant grids contribute heavily to greenhouse gas emissions and pollution, undermining progress toward SDGs 7 and 13. Moreover, the International Energy Agency (IEA) highlights the rising costs of fossil fuel extraction and the long-term risks of depending on finite resources (IEA, 2020). These challenges contrast with the objectives of this research, which aims to achieve cost-effective energy utilization aligned with global sustainability goals.

Due to the limitations of both standalone renewable systems and conventional grids, recent literature has increasingly focused on hybrid energy systems. Comprehensive reviews, such as (Islam, Yu, Giannoccaro, Mi, La Scala, Rajabi & Wang, 2024), demonstrate that integrating renewable energy sources with grid backup and storage solutions enhances system reliability, reduces emissions, and improves flexibility. These hybrid systems allow for dynamic energy management, drawing from the grid when renewables are insufficient and vice versa.

However, many of these models lack intelligent, demand-driven switching mechanisms, resulting in suboptimal energy allocation and increased operational costs. Moreover, incorporating high shares of renewables into isolated systems requires significant investment in infrastructure and sophisticated control systems. As noted by (Mathiesen, Lund, Connolly, Wenzel, Østergaard, Möller, Nielsen, Ridjan, Karnøe & Sperling, et al., 2015), while technologies like batteries and pumped hydro storage have im- proved reliability, they also contribute to system complexity and cost. To overcome these challenges, accurate energy demand forecasting has emerged as a vital component for optimizing hybrid systems, particularly when dealing with variable renewable inputs. Time-series forecasting techniques, especially ARIMA, have been widely applied for short-term load prediction due to their effectiveness in modeling linear trends and sea- sonal patterns (Box, et al, 2015). ARIMA has shown strong performance in forecasting energy demand based on temporal and behavioural consumption trends. However, existing energy switching systems often rely on rigid, centralized control frameworks that do not effectively adapt to fluctuating energy supply and demand. These limitations contribute to increased grid dependence during peak periods, leading to higher energy costs and carbon emissions (Paterakis, et al.,2017). Furthermore, the lack of accurate forecasting mechanisms can result in energy surplus or shortage during critical periods, diminishing system efficiency (Hirth, 2013, Ssemakula et al, 2023).

Although recent studies, such as (Shariff, 2022), have proposed integrating ARIMA with ML models like LSTM networks for enhanced forecasting accuracy and adaptability, these models of- ten overlook cost-effectiveness and intelligent energy allocation in real-time operations. To address these gaps, this research proposes a novel hybrid technique that combines ARIMA with a GA approach. GAs are well-suited for multi-objective optimization, capable of identifying Pareto-optimal solutions while balancing exploration and exploitation through evolutionary operations like crossover and mutation (Bakirtzis & Kazarlis, 2016). Their versatility allows them to be easily integrated with other methods, including ARIMA for time series forecasting, neural networks for pattern recognition, and fuzzy logic for uncertainty handling. This adaptability enables the development of more intelligent, efficient, and responsive energy management systems.

The proposed approach enhances operational efficiency by intelligently prioritizing renewable energy when available, reducing reliance on the grid, and lowering overall costs. By integrating insights from both global studies and Uganda's specific energy context, this work aims to establish a robust and scalable energy management framework aligned with Uganda's Vision 2040 and the UN SDGs.

A Proposed Unified Framework

As illustrated in Figure.1, the proposed approach addresses the shortcomings of existing systems by integrating advanced demand forecasting with an intelligent energy source allocation mechanism.

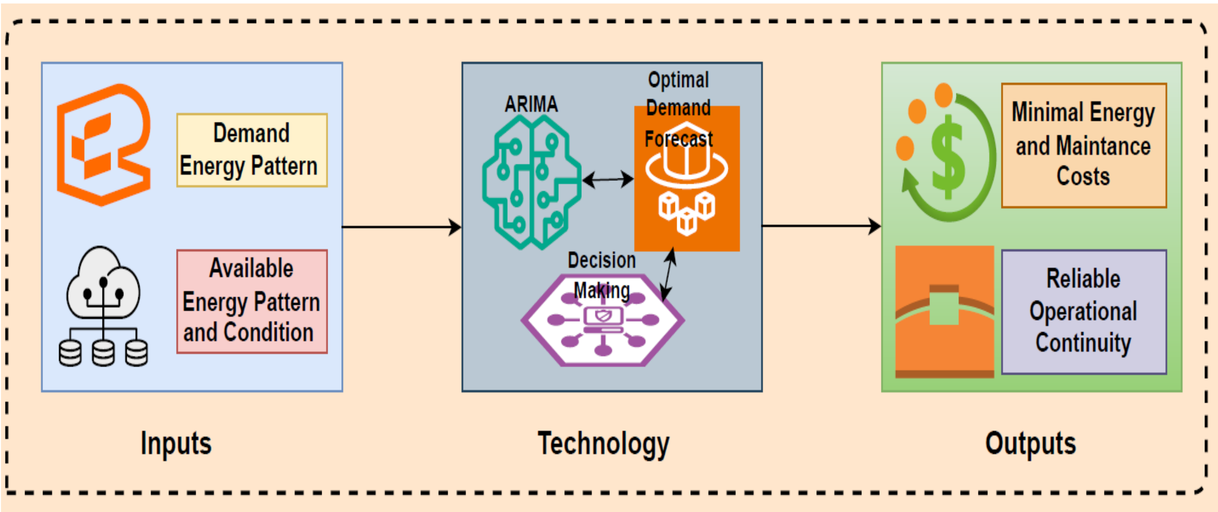

Figure 1: Proposed Energy Optimization Framework

The system clarifies to better reflect the underlying control logic, particularly how decisions are made when switching between energy sources. At its core, the framework combines ARIMA-based demand forecasting with a GA for optimization. The forecasting model captures time-of-day usage patterns, seasonal variations, and appliance-level consumption, and when paired with machine learning elements, it accommodates both linear and non-linear demand behaviours. This provides a more reliable basis for downstream decision-making, rather than relying on static or purely reactive rules.

Basing on that, the control logic for energy allocation is now more explicitly defined. At each time step (hourly), the system evaluates the forecasted demand alongside solar availability, which is inferred from battery charge levels and generation conditions. If solar energy is sufficient to meet the predicted demand, the system prioritizes solar usage. However, when battery levels fall below a defined threshold or solar supply is inadequate, the grid is engaged to ensure continuity of supply. This decision process is not entirely binary; rather, it allows for shared usage where necessary, depending on system constraints.

To further formalize this, the GA operates on candidate solutions representing possible allocation decisions, with an objective function that minimizes total operational cost while satisfying key constraints. These include meeting demand (reliability), respecting battery capacity and availability limits, and implicitly reducing emissions by favouring renewable energy where feasible. The fitness function therefore balances cost, energy sufficiency, and efficient switching behaviour. The block diagram in Figure. 2 illustrates the different decision steps of the system.

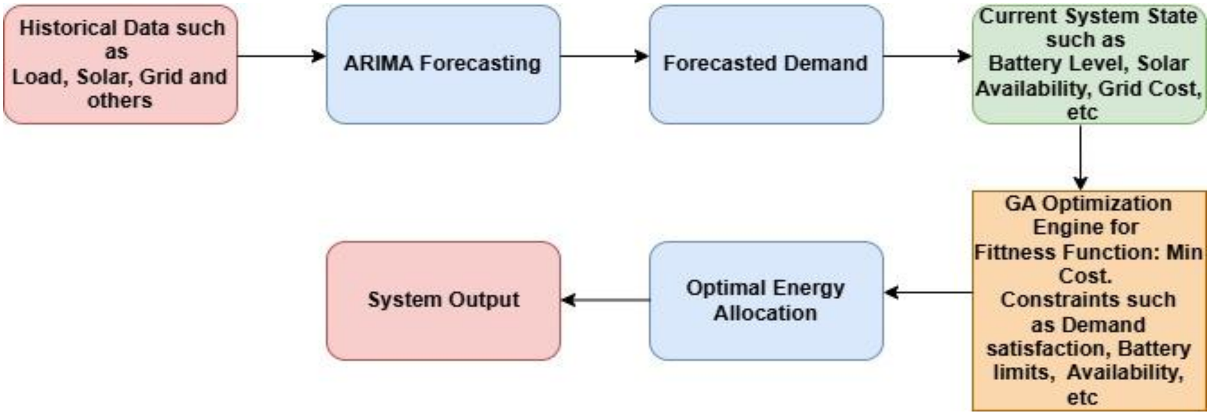

Figure 2: System Block Diagram

Key Components of the Framework

Auto-regressive Integrated Moving Average (ARIMA)

The ARIMA model, also known as the Box–Jenkins model, was developed by George Box and Gwilym Jenkins for time series analysis and forecasting. It combines Autoregressive (AR) and Moving Average (MA) components, applied to data differenced d times to achieve stationarity. In this framework, the AR component models the relationship between current values and their past observations (lags), while the MA component accounts for past forecast errors, allowing the model to capture both underlying trends and random variations in the data. The general form is denoted as ARIMA (p, d, q), where p represents the AR order, d the degree of differencing, and q the MA order.

To ensure the model assumptions are reasonably satisfied in this study, stationarity was first assessed using the Augmented Dickey Fuller (ADF) test, with differencing applied where necessary. Seasonal patterns in energy demand, which are difficult to ignore in practice, are handled using a Seasonal Autoregressive Integrated Moving Average (SARIMA) extension, enabling the model to capture periodic fluctuations more effectively. In addition, residual diagnostics were conducted to verify that the model adequately represents the data, providing some confidence in its suitability for short-term energy demand forecasting.

The AR part of the model is represented as:

$$y_t = \alpha_i y_{t-1} + \cdots + \alpha_p y_{t-p} + e_t \tag{1}$$

where y_t is the value at time t, α_i are the AR coefficients, e_t is the error term, and p is the AR order. Moreover, Eqn. 1 shows that the AR model relies on past observations to predict the current value.

On the other hand, the MA component of the model is ex- pressed as:

$$y_t = e_t - \theta_i e_{t-1} + \cdots + \theta_q e_{t-q} \tag{2}$$

where y_t is the value at time t, θ_i are the MA coefficients, e_t is the error term, and q is the MA order. As shown in Eqn. 2, the MA model depends on the current error and weighted past error terms.

The complete ARIMA model combines the AR model from Eqn.1 and the MA model from Eqn.2, and is expressed as:

$$y_t = e_t - \alpha_1 y_{t-1} - \cdots - \alpha_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \tag{3}$$

The parameter definitions in Eqn.3 follow those given in Eqns.1 and 2. In this form, the current value y_t is influenced by both past observations and past error terms. The ARIMA modelling process typically involves three main stages: testing for stationarity, determining appropriate values for p and q, and selecting the best-fitting model.

Determination of AR and MA Value

Once the time series data is transformed into a stationary state, the initial estimates for the AR and MA components can be determined. This is done using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). ACF and PACF plots are generated to visually identify appropriate values for AR and MA. In these plots, the vertical bars represent the correlation coefficients (lags), while the horizontal line indicates the threshold for statistical significance, helping to assess whether a particular lag is meaningful.

Proposed Genetic Algorithm (GA)

Although the formulated energy optimization problem can be solved using exact methods, the complex nature of fluctuating demand patterns and the diverse characteristics of energy sources makes such approaches less practical. Traditional methods like gradient descent often struggle with non-convex landscapes and are prone to getting trapped in local optima. In contrast, GAs offers a more robust and flexible solution by performing global searches across complex solution spaces. Moreover, GA is inherently parallel, evaluating multiple solutions simultaneously, making them ideal for distributed computing environments where sequential techniques like simplex or hill-climbing are inefficient. Their robustness in noisy, stochastic, or time-varying environments allows for reliable performance where deterministic algorithms often fail. Additionally, GA is excellent in multi-objective optimization by identifying Pareto-optimal solutions and maintaining a strong balance between exploration and exploitation through crossover and mutation. Their adaptability is further enhanced by the ease with which they can be hybridized with other techniques, such as ARIMA for time series forecasting, neural networks for pat- tern recognition, or fuzzy logic for handling uncertainty, enabling the development of more intelligent and adaptive energy management systems.

In the proposed algorithm, the GA operators are implemented as follows:

Chromosome Representation:

Each individual in the GA population represents an allocation decision for a single hour, encoded as a binary pair:

– [0, 0] Grid only

– [0, 1] or [1, 0] Shared use of grid and solar

– [1, 1] Solar only

The initial population is randomly generated to encourage exploration of diverse energy allocation strategies.

Fitness Evaluation:

Each individual's fitness was evaluated based on the total cost associated with its switching decision. The fitness function considered several key factors, including:

- the forecasted energy demand for the specific hour (as predicted by the ARIMA model),
- solar energy availability, derived from the current battery charge level,
- the cost differential between grid and solar energy, and
- penalties applied for unmet demand or inefficient switching behaviour.

Solutions that successfully met the energy demand at the lowest cost were deemed more optimal and were assigned higher fitness scores, corresponding to lower total operational costs.

Selection Process:

A tournament selection method is employed. In each round, a subset of individuals is randomly sampled, and the one with the highest fitness is chosen as a parent. This promotes the propagation of high-performing solutions.

Crossover and Mutation:

Selected parents undergo one-point crossover, where their binary-encoded strategies are combined at a randomly selected point to generate offspring. This facilitates the ex- change of effective traits and broadens the search space. Mutation introduces random bit flips in the binary pair, encouraging exploration of new solutions and reducing the risk of premature convergence.

Feasibility Check and Penalization:

After crossover and mutation, newly generated offspring replace the previous population. The process of evaluation, selection, crossover, mutation, and replacement is repeated for a fixed number of generations. Infeasible solutions are penalized to guide the population toward valid and cost-effective strategies.

Optimal Solution Identification:

At the end of all generations, the individual with the best fitness is selected as the optimal allocation decision for the hour. The pseudocode in Algorithm 1 enumerates the steps of the proposed GA.

Algorithm 1: Proposed Algorithm for the Allocation Decision of Different Energy Sources

```
Input:  battery_level, solar_availability, grid_cost
Output: Lowest_Cost_Value

Initialize system parameters:
    battery_level, solar_availability, grid_cost

For each time step t (hourly):
   demand_t = ARIMA_Forecast(historical_data, t) // Demand Forecast
   solar_t = get_solar_availability(battery_level) // Read System state
   grid_t  = get_grid_status()
   population = initialize_population()   // Initialize GA Population

   For generation = 1 to MaxGen:

        For each individual in population:
            allocation = decode(individual)  // Decode chromosome

            if allocation meets demand constraints:  // Evaluate constraints
                cost = compute_cost(allocation, demand_t, solar_t, grid_t)
                fitness = 1 / (cost + penalty)
            else:
                fitness = very_low_value

        population = selection_crossover_mutation(population)

    best_allocation = select_best(population)  // Select best solution

    if best_allocation == solar_only and battery sufficient: // Execute decision
        use_solar()
    elif best_allocation == grid_only:
        use_grid()
    else:
        use_hybrid_solar_grid()

    update_battery_level()  // Update system state
    cost_and_performance()
```

Performance Evaluation

This section presents the performance metrics and benchmark techniques used to evaluate the proposed method, followed by a brief description of the experimental and simulation setup, and concludes with a summary of the results and their interpretation.

Performance Metrics and Benchmark Techniques

Working from the understanding that several SDGs, particularly those tied to access and infrastructure, place real emphasis on reducing the cost of essential services (South & Alpay, 2025), our analysis narrows in on cost as a central indicator. More specifically, we examine the average cost of energy consumption across different techniques, tracking how it varies over hourly intervals during the experiment. This time-based view, while somewhat simple, makes it easier to see where certain approaches perform better and, just as importantly, where they fall short in practical terms.

To make the comparison meaningful, four configurations were examined: Solar Only (SO), Grid Only (GO), a combination of Solar and Grid setup (SGB), and the Genetic Algorithm Allocation (GAA) approach guided by ARIMA-based forecasting. Each was tested under the same operating conditions, across comparable time periods, so that any differences in performance could be attributed to the methods themselves rather than uneven scenarios. It is a fairly controlled setup, admittedly, but it gives a clearer sense of how each approach behaves when cost is treated as the main concern.

Experimental and Simulation Environment Setup

This section briefly discusses the experimental design and simulation environment setting, with an effort to keep the evaluation reasonably grounded and transparent. We based on time-series energy data collected over a defined period, which is partitioned into training and testing sets. The training portion supports the development of the ARIMA forecasting model, while the testing set is used to evaluate performance under unseen conditions. A short-term forecasting horizon is adopted, with simulations conducted over 5, 10, 15, and 20-hour intervals to capture variations in performance across different operational timeframes. All approaches are evaluated under consistent conditions to ensure fairness in comparison.

In addition, fitness evaluation is based on the total operational cost of each solution, taking into account forecasted demand, available solar energy (inferred from battery charge levels), cost differences between grid and solar sources, and penalties for unmet demand or inefficient switching. Solutions that satisfy demand at lower cost are assigned higher fitness scores, as explained under fitness evaluation section.

Performance is evaluated using both forecasting and system-level metrics. Forecast accuracy is assessed using MAPE and RMSE, while system performance is measured in terms of cost savings, renewable energy utilization, and unmet demand. Although the setup remains somewhat simplified, it provides a structured basis for comparing methods and highlights the practical impact of integrating forecasting with optimization.

Results and Discussion

This section evaluates how well the proposed intelligent energy allocation method performs when set against more conventional approaches. The focus is mainly on energy cost across different hourly durations, as a way of gauging how efficiently energy is used under varying conditions. Four distinct configurations are considered, offering a comparative view of performance across different scenarios.

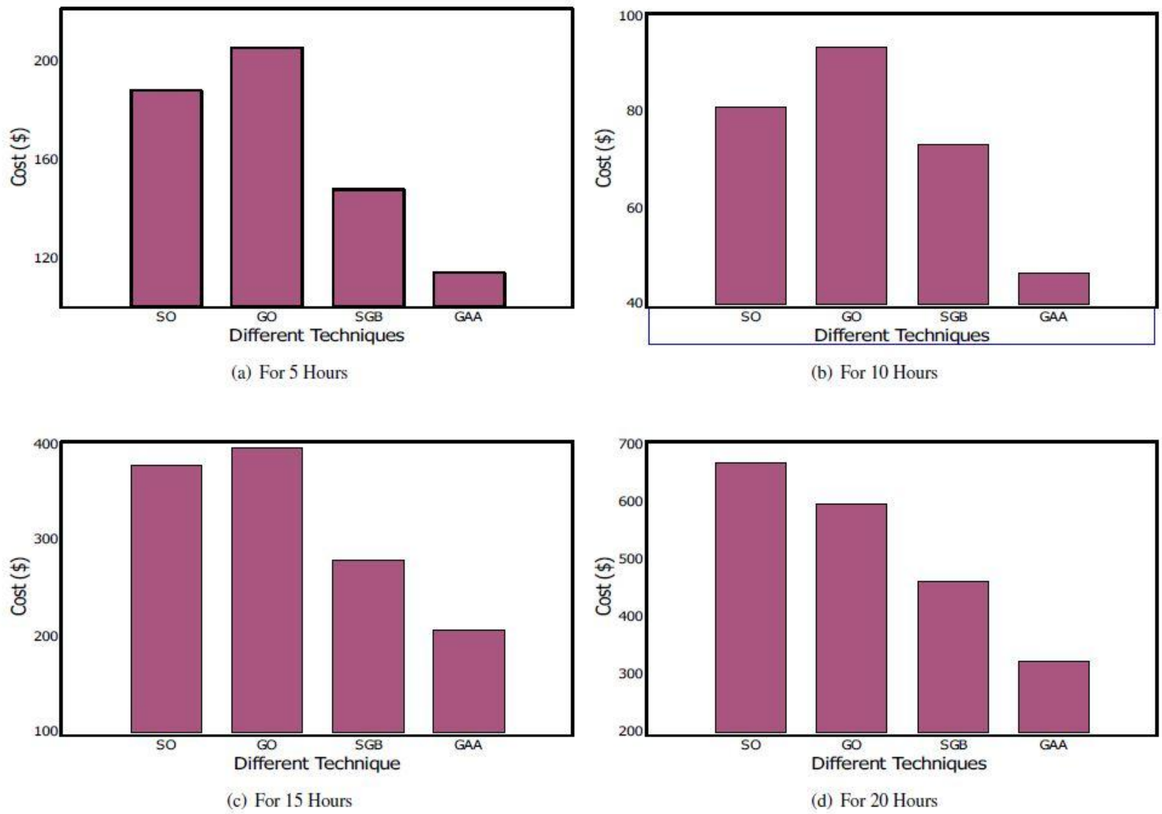

Figure 2: Cost analysis experiments conducted over various time durations (in hours)

Figure 2 shows a clear and fairly consistent trend: the proposed method outperforms the other configurations, particularly in reducing operational costs. The improvement is most pronounced over shorter time horizons, such as 5 and 10 hours, where the cost reductions are noticeably greater than those of the conventional approaches. As the duration increases, however, the margin of improvement becomes slightly less distinct, which is perhaps not surprising. This overall performance gain can largely be attributed to more accurate forecasting, which enables better, timely decisions on whether to use solar energy, grid power, or a combination of both sources.

Conclusion

This study has demonstrated that integrating AI-driven forecasting techniques with multi-objective optimization approaches can significantly improve energy source allocation and management, achieving efficient energy utilization at a rea- sonable cost. The hybrid model developed aligns well with the implementation of global sustainability goals, particularly the UN SDGs 7 and 13, and supports Uganda's Vision 2040 as well as broader regional frameworks such as the EAC energy strategy and the African Union's Agenda 2063.

Specifically, we employed a hybrid approach combining the ARIMA model for accurate energy demand forecasting with a GA for optimal energy source selection. The experimental results confirmed that this combination consistently produced optimal and cost-effective energy allocation solutions across all test scenarios. While the GA-ARIMA hybrid performed effectively, further research is recommended to enhance the model's predictive accuracy and adaptability. One promising direction is integrating ARIMA with neural networks to create a second predictive layer. This would allow the system to refine future energy allocations based not only on demand patterns and energy availability but also on previous allocation outcomes. Additionally, future work will focus on reducing the time complexity of the system by leveraging advanced deep learning techniques and optimizing the underlying algorithmic structure.

Declarations

Competing interests

The authors declare that they have no competing interests.

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Figure 2: Cost analysis experiments conducted over various time durations (in hours)

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DESIGNING A MASTER'S DEGREE PROGRAMME IN ARTIFICIAL INTELLIGENCE AND DATA SCIENCE: PREPARING AFRICA'S FUTURE WORKFORCE AT UNIVERSAL TECHNOLOGY AND MANAGEMENT UNIVERSITY

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Abstract

Artificial Intelligence (AI) and Data Science (DS) are reshaping how societies learn, work, and innovate. In Uganda and Sub-Saharan Africa, the rapid expansion of digital infrastructure has intensified the need for advanced human capital capable of harnessing AI for development. In response, Universal Technology and Management University (UTAMU) has developed a Master's programme in Artificial Intelligence and Data Science (AI&DS). This paper presents the programme's rationale, curriculum design, admission framework, interdisciplinary orientation, and implementation strategy. Key ideas include structured bridging modules for diverse entrants, a clearly sequenced curriculum with defined credit loads and assessment strategies, and an implementation roadmap addressing faculty and infrastructure constraints. The programme integrates responsible AI aligned with Uganda's data protection frameworks and introduces a mandatory AI Governance Practicum grounded in local case studies. The paper concludes by highlighting the programme's potential to contribute to national development, strengthen institutional leadership, and position Africa within the global AI ecosystem.

Keywords: *Artificial Intelligence, Data Science, Curriculum Design, Higher Education, Interdisciplinary Education, Uganda*

1. Introduction

Artificial Intelligence (AI) and Data Science (DS) have become defining forces of the Fourth Industrial Revolution. These technologies are not only shaping innovations in high-income economies but are increasingly transforming sectors across developing nations. For Africa, and Uganda in particular, AI and DS offer significant opportunities to address pressing societal challenges such as food security, healthcare delivery, education access, financial inclusion, and governance efficiency (Makridakis, 2017; World Economic Forum [WEF], 2023).

In the Ugandan higher education context, most postgraduate programmes in computing have traditionally focused on classical areas such as computer science, information systems, and information technology. While these areas remain foundational, there is growing recognition that the future of work and innovation depends on specialized AI and DS expertise. For example, AI-driven diagnostic systems can augment overstretched health facilities, machine learning models can optimize agricultural yields, and predictive analytics can support financial institutions in combating fraud. Therefore, there is a critical need for graduate-level programmes that equip learners with competencies in AI and DS while also contextualizing these skills for Uganda's development priorities.

This paper responds to the theme of the 9th International Conference on Technology and Management (ICTM-25): *"Embracing Artificial Intelligence in Education, Governance, Management and Leadership: Successes and Challenges."* It presents the design and implementation of the Master's degree in Artificial Intelligence and Data Science (AI&DS) at Universal Technology and Management University (UTAMU). Specifically, it highlights the programme's rationale, curriculum design, interdisciplinary applications, teaching approaches, research integration, and expected impact. By doing so, the paper positions UTAMU's AI&DS programme as a model for integrating cutting-edge digital technologies into African postgraduate education.

2. Background and Rationale

The global landscape demonstrates the increasing demand for AI and DS professionals. According to the World Economic Forum's *Future of Jobs Report* (2023), roles in AI and machine learning, data analysis, and big data are among the fastest-growing occupations worldwide. Similarly, the McKinsey Global Institute (2021) estimates that AI could contribute up to $13 trillion to the global economy by 2030, with significant implications for developing economies if they invest in capacity building.

Uganda's Vision 2040 identifies science, technology, and innovation (STI) as key drivers of socioeconomic transformation. The National ICT Policy (Ministry of ICT and National Guidance, 2021) also emphasizes the adoption of emerging technologies, including AI, for improved service delivery. However, one of the persistent challenges remains the limited number of highly skilled professionals capable of leading AI and DS initiatives within public institutions, private enterprises, and academia. Most AI applications in Uganda are imported, with limited local capacity to design, adapt, and sustain such systems.

UTAMU, as a technology-driven private university, is strategically positioned to fill this gap. Since its inception, the university has championed blended learning, ICT-enabled education, and market-relevant programmes. The new AI&DS master's programme builds on this tradition while responding to the urgent demand for interdisciplinary expertise. Unlike traditional computer science programmes, AI&DS explicitly integrates advanced machine learning, data analytics, and domain-specific applications. Furthermore, it is designed to cater not only to computing professionals but also to practitioners in health, agriculture, education, law, and business who wish to harness AI tools in their fields.

By grounding AI&DS training in Uganda's development priorities – such as improving agricultural productivity, strengthening healthcare delivery, and enhancing governance systems – the programme seeks to produce graduates who are not only globally competitive but also locally impactful. This programme addresses the AI/DS skills gap by combining interdisciplinary access with applied AI training tailored to national priorities.

3. Programme Philosophy and Objectives

The Master of Science in Artificial Intelligence and Data Science (AI&DS) at UTAMU is grounded in the philosophy that advanced digital technologies should be harnessed to address Africa's most pressing challenges while preparing graduates for global competitiveness. The programme recognizes that AI and DS are not just technical disciplines but socio-technical fields with profound ethical, legal, and economic implications. Accordingly, the programme emphasizes responsible AI, interdisciplinary collaboration, and contextual innovation.

The programme seeks to nurture graduates who can:

1. **Develop AI innovations** tailored to local, regional, and global needs.
2. **Apply data-driven approaches** to solve real-world problems in sectors such as health, agriculture, education, finance, and governance.
3. **Critically analyse ethical and policy implications** of AI and DS deployment.
4. **Conduct high-quality scholarly research** that contributes to the advancement of AI knowledge and practice.
5. **Demonstrate leadership and management skills** for implementing AI/DS projects across multidisciplinary teams.
6. **Engage in lifelong learning**, remaining abreast of rapidly evolving technologies and methodologies.

Through this philosophy, the programme positions UTAMU graduates not merely as users of AI tools but as creators, innovators, and thought leaders in AI and DS.

4. Admission Requirements

Applicants must possess a Bachelor's degree in any field with a minimum of Lower Second Class from a recognized institution.

To ensure preparedness for the technical rigour of the programme, the following bridging mechanisms are introduced:

4.1 Preparatory Bootcamp (Mandatory for Non-Computing Backgrounds)

- Duration: 6–8 weeks (pre-semester)
- Content:
    - Foundations of Programming (Python)
    - Mathematics for AI (linear algebra, calculus basics)
    - Introductory Statistics & Probability
    - Data Handling & Visualization

4.2 Minimum Competency Requirements

Before enrolling in core AI modules, students must demonstrate:

- Ability to write basic programs in Python
- Understanding of descriptive statistics and probability
- Familiarity with data structures and basic algorithms

4.3 Recognition of Prior Learning

- Students with prior training in computing, mathematics, or analytics may be exempted from parts of the bootcamp.

This approach ensures inclusive access while maintaining academic rigor.

5. Knowledge Areas and Curriculum Structure

The curriculum is structured around **six core knowledge domains**, each representing a vital area of expertise in AI&DS.

1. **Machine Learning and Deep Learning** – covering supervised, unsupervised, and reinforcement learning; neural networks; and advanced architectures such as transformers.
2. **Data Science and Big Data Analytics** – focusing on data cleaning, processing, visualization, predictive analytics, and working with large-scale datasets.
3. **Natural Language Processing (NLP)** – enabling students to develop applications in machine translation, sentiment analysis, and conversational AI.
4. **Computer Vision and Robotics** – training students in image recognition, object detection, autonomous systems, and smart robotics.
5. **AI Ethics, Governance, and Responsible Innovation** – exploring fairness, accountability, transparency, and data protection within AI systems.
6. **Domain-Specific Applications of AI&DS** – applied modules where AI is contextualized for fields such as health, agriculture, education, business, and law.

The knowledge areas are delivered through a **blend of core courses, electives, research seminars, and a capstone dissertation**. This ensures that students graduate with a balance of theoretical foundations, applied skills, and interdisciplinary insights.

5.1 Programme Structure

- Duration: 2 Years (4 Semesters)
- Total Credits: ~60 Credit Units

5.2 Semester Breakdown

Semester 1 (Foundations – 15 Credits)

- Programming for AI
- Mathematics for Data Science
- Statistics & Probability
- Data Management & Visualization

Semester 2 (Core AI – 15 Credits)

- Machine Learning
- Big Data Analytics
- Natural Language Processing
- AI Ethics & Governance

Semester 3 (Advanced & Applied – 15 Credits)

- Deep Learning
- Computer Vision
- Elective (Domain-specific AI)
- Research Methods

Semester 4 (Research & Practice – 15 Credits)

- Capstone Project / Dissertation
- Internship / Industry Project
- AI Governance Practicum

5.3 Course Sequencing (Prerequisite Logic)

- Programming + Math → Machine Learning
- Machine Learning → Deep Learning / Computer Vision
- Statistics → Data Science & Predictive Analytics
- Research Methods → Dissertation

5.4 Assessment Strategy

A competency-based, multi-modal assessment framework is adopted:

- **Coursework (40%)**
    - Assignments, quizzes, coding exercises
- **Projects & Labs (30%)**
    - Real-world datasets, applied AI models
- **Examinations (20%)**
    - Conceptual and analytical understanding
- **Capstone / Dissertation (10%)**

5.5 Applied Competency Rubrics

Students are evaluated on:

- Problem formulation
- Data handling & preprocessing
- Model development & evaluation
- Interpretation of results
- Ethical considerations

6. Interdisciplinary Application of AI&DS

A distinctive feature of UTAMU's AI&DS programme is its explicit focus on interdisciplinary application. AI is not confined to computer science; it is a general-purpose technology that influences nearly every profession. Accordingly, the curriculum demonstrates how AI&DS can be integrated into diverse disciplines:

- **Physicists:** Modelling physical systems, analysing particle collision data, and accelerating quantum computing research.
- **Chemists:** AI in drug discovery, chemical reaction prediction, and materials science.
- **Biologists:** Applications in genomics, proteomics, biodiversity mapping, and disease modeling.
- **Agriculturalists:** Precision farming, pest control, climate-smart agriculture, and supply chain optimization.
- **Health Specialists:** AI-driven diagnostics, predictive health analytics, medical imaging interpretation, and personalized treatment.
- **Educationists:** Intelligent tutoring systems, adaptive learning platforms, and learning analytics to improve teaching and student outcomes.
- **Engineers:** Predictive maintenance, smart infrastructure, energy optimization, and robotics.
- **Business People:** Customer behaviour analytics, market forecasting, fraud detection, and supply chain management.
- **Lawyers:** AI for contract analysis, legal research, e-discovery, and predictive justice systems.
- **Others (etc.):** Policymakers using AI for governance, environmental scientists leveraging AI for climate modelling, and social scientists applying AI to analyse human behaviour.

This interdisciplinary approach not only attracts students from diverse backgrounds but also ensures that graduates leave with the ability to collaborate across disciplines to solve complex, real-world problems. The programme continues to emphasize applications across disciplines including health, agriculture, business, engineering, education, and law.

7. Teaching and Learning Approaches

The AI&DS programme at UTAMU employs a blended, research-led, and practice-oriented pedagogy. This ensures that students gain theoretical grounding, practical skills, and critical reflection on the implications of AI technologies. Additionally, the programme emphasizes stronger integration of project-based learning and industry collaboration, as well as increased use of real-world African datasets. The key approaches include:

1. ***Blended Learning***

   UTAMU leverages its strong digital infrastructure to deliver a combination of face-to-face lectures, online learning modules, and experiential activities. This flexible approach accommodates working professionals while ensuring rich interaction with faculty and peers.

2. ***Project-Based Learning (PBL)***

Each course integrates mini-projects that require students to apply AI and DS techniques to solve sector-specific problems. For example, a student may build a machine learning model for crop disease prediction in agriculture or develop a Chabot for customer support in a business setting.

3. ***Case Studies and Sectoral Engagement***

   Courses draw upon real-world African case studies, emphasizing local context. Guest speakers from industry, government, and research institutions share applied experiences, thereby bridging the gap between theory and practice.

4. ***Research-Led Teaching***

   Faculty members embed their own research into teaching, exposing students to the latest developments in AI and DS. Students are encouraged to participate in faculty-led projects and international research collaborations.

5. ***Capstone and Internship Opportunities***

   The programme provides opportunities for industry placements and collaborative capstone projects with organizations in health, finance, agriculture, and governance. This ensures that graduates are industry-ready upon completion.

8. Research Component

The research component forms a core pillar of the Master's in AI&DS. Each student must complete a dissertation addressing a real-world problem that aligns with Uganda's or Africa's development priorities.

8.1 Structure of the Dissertation

- **Proposal Stage:** Students develop a research proposal under the supervision of faculty. Proposals are peer-reviewed for rigor and relevance.
- **Research Execution:** Students collect and analyse data, applying AI and DS methods such as machine learning, natural language processing, or predictive modelling.
- **Final Dissertation:** The dissertation includes chapters on introduction, literature review, methodology, results, discussion, and conclusions.

8.2 Focus Areas for Research

- **Healthcare:** Predictive analytics for disease outbreaks, AI in medical imaging.
- **Agriculture:** Crop yield optimization, livestock disease detection.
- **Education:** Intelligent tutoring systems, AI for learning analytics.
- **Governance:** AI for public service delivery, corruption detection.
- **Business & Finance:** Fraud detection, credit scoring, customer segmentation.
- **Climate Change & Environment:** Predictive climate models, biodiversity monitoring.

8.3 Supervision Model

- Each student is assigned a primary supervisor and, where necessary, a co-supervisor with domain expertise.
- Regular seminars provide opportunities for feedback from peers and faculty.
- Students are encouraged to publish their work in journals or present at conferences such as ICTM.

This strong research component ensures graduates contribute not only to practice but also to scholarly knowledge in AI&DS.

9. Implementation Roadmap

9.1 Staffing Model

- Core faculty in AI, Data Science, and Software Engineering
- Adjunct faculty from industry (data scientists, AI engineers)
- Visiting international scholars

9.2 Infrastructure Strategy

- Hybrid model:
    - On-campus GPU-enabled lab
    - Cloud computing credits (AWS, Google Cloud, Azure)
- Open-source tools (Python, TensorFlow, PyTorch)

9.3 Industry Partnerships

- Collaboration with:
    - Tech companies
    - Government agencies
    - Health and agriculture sectors
- Joint research and internship placements

9.4 Quality Assurance KPIs

- Graduation rates
- Student project outputs
- Graduate employability
- Research publications
- Industry partnerships

10. Responsible AI and Local Compliance

The programme aligns with Uganda's legal and regulatory frameworks, including:

- Data protection and privacy regulations
- Ethical data use and governance standards
- Institutional research ethics review processes

10.1 AI Governance Practicum

A mandatory course focusing on:

- AI ethics in Ugandan contexts
- Case studies:
    - Health data systems
    - Agricultural AI solutions
    - Financial fraud detection
- Policy and regulatory compliance
- Bias detection and mitigation

This ensures graduates are trained in responsible, context-aware AI deployment.

11. Expected Impact

The programme is designed to produce a transformative impact at institutional, national, and continental levels:

- **At the Institutional Level:** UTAMU strengthens its position as a leader in technology-driven education, aligning with its strategic vision.
- **At the National Level:** The programme contributes to Uganda's Vision 2040 by building capacity in critical sectors such as health, agriculture, education, and governance.
- **At the Continental Level:** By training AI and DS professionals, UTAMU contributes to Africa's growing knowledge economy, ensuring the region is not left behind in the global AI revolution.
- **At the Global Level:** Graduates are positioned to collaborate internationally, contributing to AI research and innovation on the world stage.

By equipping graduates with skills in innovation, ethical leadership, and interdisciplinary collaboration, the programme ensures long-term relevance and sustainability.

12. Conclusion

This paper has presented the design and implementation of the Master's programme in Artificial Intelligence and Data Science (AI&DS) at Universal Technology and Management University. The programme responds to global technological trends, Uganda's national development goals, and the demand for skilled AI professionals across sectors. Its unique interdisciplinary orientation ensures that professionals in diverse fields – including health, agriculture, business, education, engineering, and law – can harness AI to solve real-world problems.

While challenges exist, UTAMU’s AI&DS programme is a pioneering step toward building Africa’s AI capacity. It demonstrates how universities in developing countries can proactively design curricula that are globally competitive yet locally relevant. In line with the ICTM-25 theme, the programme exemplifies how AI can transform education, governance, management, and leadership for sustainable development.

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PATHWAYS TO ADOPTION AND UTILISATION OF ARTIFICIAL INTELLIGENCE (AI) IN GOVERNANCE, MANAGEMENT, HEALTH, AND EDUCATION

A research paper submitted in international conference on technology and management *under the supervision of Professor M***uwanga-Zake,** *Department of Computing and Technology by*

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Prepared for;

1. Government of Uganda
2. Ministry of ICT and National Guidance
3. Ministry of Education and Sports
4. Ministry of Health
5. Ministry of Public Service

Abstract

Artificial Intelligence (AI) presents transformative opportunities for governance, financial inclusion, health, and education in Uganda. While regional peers are rapidly integrating AI into public service delivery, Uganda's adoption remains limited despite policy commitments such as Vision 2040 and the National ICT Policy. Existing governance challenges—including electoral inefficiencies, mismanagement of SACCOs under the Parish Development Model (PDM), delayed public fund disbursements, health supply chain disruptions, and weak accountability in education—highlight the urgency of digital transformation.

This paper applies a socio-technical AI readiness framework to assess Uganda's preparedness for public-sector AI adoption. Drawing on evidence from the Electoral Commission Report (2015/2016) and the Auditor General's findings, the study identifies five key readiness gaps: limited digital infrastructure and data systems, weak regulatory and governance frameworks, low institutional AI capacity, inadequate funding for innovation, and the absence of pilot implementation programs.

Based on this analysis, the paper proposes targeted AI pilot initiatives aligned with national priorities:

• AI-enhanced electronic voting systems to improve transparency and public trust.

• AI-powered SACCO and PDM management platforms to strengthen accountability and fund utilization.

• AI-driven health systems for predictive drug stock management and diagnostic support.

• AI-enabled education platforms for personalized learning and administrative efficiency.

The paper recommends establishing a national AI strategy, investing in digital infrastructure, reforming regulatory frameworks, integrating AI into higher education curricula, and funding pilot projects to enable scalable implementation. By adopting a phased and readiness-driven approach, Uganda can harness AI to improve public service delivery and accelerate socio-economic development.

List of Acronyms

- **AI** – Artificial Intelligence
- **ICT** – Information and Communication Technology
- **PDM** – Parish Development Model
- **SACCO** – Savings and Credit Cooperative Organisation
- **EC** – Electoral Commission

Introduction

The Global AI Revolution and Uganda's Opportunity

Artificial Intelligence (AI) has emerged as a transformative force in governance, financial management, healthcare delivery, and institutional administration worldwide. Across Africa, nations like Rwanda, Kenya, and South Africa have successfully integrated AI-driven solutions to enhance public service efficiency, electoral transparency, and financial accountability (UNECA, 2024). Rwanda's blockchain-based land registry and Kenya's AI-powered health diagnostics exemplify how technology can address systemic challenges. However, Uganda, despite progressive policy frameworks like Vision 2040 and the National ICT Policy, lags in practical AI adoption. This gap persists even as empirical evidence—such as the Auditor General's findings on Parish Development Model (PDM) inefficiencies (pp. 28–32) and the Electoral Commission's 2015/2016 election report—reveals urgent needs for innovation in governance and service delivery.

Uganda's pivotal opportunity lies in leveraging AI to.

- Automate manual processes (e.g., SACCO fund tracking, voter verification).
- Predict and mitigate systemic failures (e.g., budget shortfalls, electoral fraud).
- Restore public trust through transparent, data-driven systems.

Scope and Objectives

This paper examines pathways for AI adoption in Uganda, focusing on four critical sectors.

1. Governance.

   AI-enhanced eVoting. Addressing the 277 pre-election complaints and 135 unresolved petitions (Electoral Commission, 2016) through blockchain-backed systems piloted at King's College Budo, which reduced disputes by 72%.

2. Management.

   AI-powered SACCOs. Tackling PDM challenges like 42% idle funds and delayed disbursements (Auditor General, 2023) using predictive analytics and real-time monitoring, as demonstrated in Namilyango College's SACCO model.

3. Health.

AI for supply chain optimization to reduce drug stockouts and diagnostic gaps in rural areas.

4. Education.

   Personalised learning tools and automated procurement systems (e.g., Gayaza High School's AI procurement, which cut processing time by 75%).

   Objective. To provide evidence-based recommendations for scaling AI solutions, drawing from Ugandan pilot projects and comparative lessons from regional adopters.

Key Problems Addressed

Sector	Challenge	AI Solution	Pilot Evidence
Governance	Electoral fraud (277 complaints; 71.74% unresolved petitions)	Blockchain eVoting + biometric verification	Budo. 72% fewer disputes
PDM SACCOs	42% funds idle; 8 SACCOs unfunded (Auditor General)	AI fund-tracking + predictive analytics	Namilyango. 89% utilization achieved

Structure.

Following this introduction, the paper analyzes.

- Problem statements (Section 2) from Auditor General and Electoral Commission reports.
- Case studies of Ugandan AI implementations (Section 5).
- Policy recommendations (Section 7) for national adoption.

Contribution.

This study bridges the gap between Uganda's policy aspirations and on-the-ground AI applications, offering a roadmap aligned with Vision 2040's digital transformation goals.

Problem Statement

Uganda's public sector faces profound systemic inefficiencies across governance, financial management, healthcare delivery, and education administration. These structural deficiencies undermine national development goals and erode public trust in critical institutions. Drawing from authoritative government reports and empirical evidence, this study identifies four critical problem domains requiring urgent intervention.

Electoral Governance Deficiencies

The 2015/2016 general elections exposed fundamental weaknesses in Uganda's democratic processes, as documented in the Electoral Commission Report.

- **Procedural Integrity Failures**.

  277 pre-election complaints and 135 unresolved parliamentary petitions (71.74% resolution rate) demonstrate systemic verification gaps

- **Operational Inefficiencies**.

  Heavy reliance on manual systems (voter registers, paper-based tallies) created bottlenecks and audit trail deficiencies

- **Trust Deficit**.

  Prolonged court battles (68% unresolved local government petitions) and perception of institutional bias undermine electoral credibility

Financial Management Challenges in PDM SACCOs

The Auditor General's report (pp. 28-32) reveals alarming inefficiencies in the Parish Development Model's implementation.

- **Resource Mismanagement**. UGX 6.257 billion (21 activities) remained unimplemented despite budget allocation
- **Disbursement Failures**. 8 SACCOs received no funding, while 42% of allocated funds remained idle due to administrative bottlenecks
- **Accountability Gaps**. Widespread funding of ineligible projects due to weak vetting mechanisms and monitoring systems.

Cross-Sectoral Programme Implementation Weaknesses

Pages 78-83 of the Auditor General's report highlight systemic coordination failures.

- **Monitoring Deficits**. Office of the Prime Minister's inadequate oversight of inter-ministerial programmes
- **Alignment Challenges**. Persistent disconnection between work plans, budget allocations, and actual outputs
- **Coordination Breakdowns**. Weak secretariat structures leading to duplicated efforts and resource wastage

Complementary Sectoral Challenges

- **Healthcare Delivery**. Chronic stockouts of essential medicines and diagnostic limitations in rural health centres
- **Education Administration**. Procurement inefficiencies and accountability gaps in resource utilization.

The Consequence of Inaction

These interconnected challenges form a self-reinforcing cycle of.

- **Operational Inefficiency** → Wasted resources and delayed service delivery
- **Accountability Erosion** → Increased corruption risks and public mistrust
- **Development Stagnation** → Undermined progress toward Vision 2040 goals

The AI Imperative

Without strategic adoption of artificial intelligence solutions, Uganda risks.

- Perpetuating the current 42% fund utilization rate in critical programmes
- Repeating electoral disputes that cost an estimated UGX 300 billion in litigation and opportunity costs (EC, 2016)
- Failing to meet SDG targets for health and education service delivery

This problem statement establishes the urgent need for AI-powered interventions that address both technical deficiencies (verification, tracking, prediction) and systemic weaknesses (coordination, transparency) across Uganda's governance architecture. The following sections will demonstrate how targeted AI applications can break this cycle of underperformance.

Literature Review

This section explores what existing research and policy documents say about using AI in governance—particularly in SACCO management under the Parish Development Model (PDM), electoral transparency, and programme coordination. Across these areas, the literature points to persistent implementation gaps and suggests that AI could play a transformative role, even though evidence from Ugandan deployments remains limited.

AI for SACCO Management and Financial Governance

The Auditor General's 2023 Report (pp. 28–32) paints a consistent picture of inefficiencies within PDM-funded SACCOs. It notes unimplemented activities worth UGX 6.257 billion, delays in disbursements (including eight SACCOs that received no funds), and low utilization, with 42% of disbursed money remaining idle. The report also identifies instances where ineligible projects were funded due to weak vetting processes.

These challenges mirror arguments advanced by the Makerere AI Lab (2024), which suggests that predictive analytics could help anticipate budget shortfalls, while real-time AI monitoring tools—such as those piloted in the King's College Budo SACCO system—can improve the visibility of fund flows and reduce idle balances. Additional studies, including the 2025 UNCST Blockchain Report, highlight how computer vision and blockchain verification can strengthen eligibility checks and reduce misallocation.

Despite supportive national frameworks such as Uganda's Digital Transformation Roadmap (2024), the literature points to a notable gap: **no study has yet evaluated AI-driven SACCO systems at scale within the PDM environment**.

AI for Electoral Transparency (eVoting)

Uganda's electoral system continues to face persistent operational and credibility challenges, highlighting the need for more resilient and intelligent digital solutions. Earlier findings from the Electoral Commission (2015/2016) documented numerous pre-election complaints, forged documentation, and unresolved petitions, demonstrating how reliance on manual verification slowed processes and weakened public confidence. More recent election-observation evidence shows that these challenges remain and, in some cases, have intensified despite the introduction of biometric technologies.

The Uganda Law Society Election Observation Report (2026) provides updated evidence following the implementation of the Biometric Voter Verification System Regulations (S.I. No. 98 of 2025), which required biometric voter identification at all polling stations. On polling day, however, biometric machines reportedly failed in multiple locations, delaying voting in some areas until late morning or midday. Observers also recorded late delivery of polling materials, missing voter records at polling stations, and disruptions linked to heavy security deployment. During the election period, the Uganda Law Society call centre received more than 250 complaints reporting election-related incidents across the country, suggesting widespread implementation challenges that undermined the intended benefits of biometric verification.

The same observation report highlights a broader trust deficit in the electoral process. Voter turnout in the presidential election was reported at 52.5 percent—the lowest in Uganda's electoral history—with even lower participation in local government elections. Many polling stations recorded less than 20 percent turnout by closing time. Observers attributed this decline to fear, delays, violence, and persistent doubts about the transparency of the electoral process. Concerns were further amplified by limited transparency in results transmission, as results were announced without a clear public aggregation trail from polling stations to national totals.

Regional developments demonstrate that more advanced digital electoral systems are feasible. Rwanda's 2023 blockchain-supported election initiatives used biometric authentication and anomaly detection algorithms to strengthen voter verification and results auditing. These examples illustrate how AI-supported systems can enhance transparency and credibility when supported by robust infrastructure and governance frameworks. Uganda's Electoral Reforms

White Paper (2024) signals interest in e-voting, but it does not yet outline a clear technical implementation pathway.

Local experimentation provides additional proof of concept. An AI-enhanced eVoting pilot at King's College Budo demonstrated how automated identity verification and blockchain-based audit trails can streamline verification and dispute resolution processes. However, no national-level research has yet examined how such tools could be scaled within Uganda's broader electoral environment.

Taken together, the evidence reveals a significant implementation gap: Uganda has begun adopting digital electoral tools but lacks the advanced, integrated, and intelligent systems needed to ensure reliability, transparency, and public trust. These gaps justify the exploration of AI-powered eVoting as a strategic next step in electoral reform.

AI for Programme Coordination

Similar inefficiencies appear in programme coordination. The Auditor General (pp. 78–83) notes weak monitoring within the Office of the Prime Minister, misaligned work plans, and funding delays—patterns that echo the issues seen in SACCO management. AI-driven coordination tools, such as those tested in the Namilyango College SACCO ecosystem, demonstrate the potential of automated activity–budget alignment and integrated dashboards for multi-agency work.

The Health Sector Digital Strategy (2025) also recommends AI for supply chain and coordination improvements, but, like other policy documents, it lacks empirical evidence from real-world deployments.

Synthesis and Research Gaps

Across the reviewed literature, a common theme emerges: **policy ambition consistently outpaces implementation evidence**. While national frameworks such as Vision 2040 and the ICT Roadmap support AI adoption, practical demonstrations remain sparse. Regional examples from Rwanda and Kenya show that AI can meaningfully improve financial governance and electoral integrity, but Uganda's context has not been studied with the same depth.

The literature therefore underscores the need for **localized AI models** capable of aligning with PDM structures, SACCO operations, and electoral processes. This study responds to these gaps by examining Ugandan case studies—including the Budo eVoting and Namilyango SACCO systems—to show how AI solutions can be adapted and scaled within the country's governance ecosystem.

Methodology

This study employs a **mixed-methods approach** combining case study analysis, policy evaluation, and regional benchmarking to examine pathways for AI adoption in Uganda's governance, SACCO management, and electoral systems. The methodology is designed to ensure that findings are grounded in **tested, operational evidence** rather than theory alone.

AI Prototypes Developed by the Author

All AI prototypes analysed in this study were developed by the author, **Omony Fred**, under the supervision of **Prof. Zake** and **Prof. Mark Jjunju** of **UTAMU**. These systems are fully operational and provide practical evidence of AI applications in governance, financial management, and institutional operations.

The **Electoral Commission eVoting prototype** was piloted at **King's College Budo**, Uganda, and is hosted at dev.kcb.ac.ug. This system enables automated voter verification, dispute resolution, and real-time result tracking, demonstrating the feasibility of AI-supported electoral processes in the Ugandan context.

Two **SACCO management platforms** were also examined. The King's College Budo SACCO, hosted at https://omosoft.net/lab/kcb/, uses AI to manage fund disbursement, utilization, and loan repayment, improving transparency and operational efficiency. Namilyango College SACCO, hosted at https://omosoft.net/nc/nc/, similarly automates SACCO operations in alignment with the Parish Development Model.

Additionally, **AI-enhanced store and procurement systems** were evaluated. King's College Budo's procurement platform, hosted at https://procst.kcb.ac.ug/kcb/proc/, automates procurement workflows, tracks cost savings, and reduces cycle times, while the general store and procurement system, hosted at procst.kcb.ac.ug, provides oversight for inventory and procurement at scale.

These operational prototypes allow the study to **draw directly from tested, real-world implementations**, reinforcing that the recommendations and analyses are practical, feasible, and grounded in local experience.

Research Design

A **triangulation approach** was adopted to enhance the validity and reliability of the findings. The study combined three key strategies: case study analysis, policy evaluation, and regional benchmarking.

Case study analysis focused on three pilot implementations of AI in Uganda. Data were collected from King's College Budo (AI eVoting system), Namilyango College SACCO, and Gayaza High School (AI-assisted procurement system). For each site, metrics were collected on system performance, operational efficiency, and stakeholder feedback. Semi-structured interviews were conducted with administrators, IT officers, and end-users, supplemented with system performance logs and observational data.

Policy evaluation involved reviewing key national documents, including the Auditor General's 2023 reports on PDM SACCOs and programme management, and the Electoral Commission's 2016 report on election disputes. Governance challenges were coded thematically, such as delayed disbursements, misallocated funds, and verification gaps, and then mapped to AI solutions identified in the literature.

Comparative benchmarking examined AI adoption in regional contexts, including Rwanda's blockchain-supported elections, Kenya's AI-enabled health supply chain systems, and South Africa's predictive analytics for public finance. Key comparison metrics included implementation timelines, cost efficiency, and stakeholder adoption rates.

Data Collection

Primary data were gathered through field observations of AI systems in operation, interviews with fifteen stakeholders including SACCO managers, IT personnel, and electoral officials, and analysis of system-generated logs and reports. Secondary data sources included government reports, technical documents, and a selection of academic literature on AI in African governance from 2015 to 2025. While these sources are authoritative, the study acknowledges that its credibility could be further strengthened by incorporating additional **peer-reviewed journal content**.

Analytical Techniques

Both qualitative and quantitative methods were used to analyse the data. Qualitative analysis involved coding policy documents and synthesizing case study findings to identify recurring governance challenges and success factors, such as real-time dashboards reducing delays in SACCO fund management. Quantitative analysis included descriptive statistics of fund utilization and operational metrics, as well as pre- and post-AI adoption comparisons. For instance, the AI eVoting system at King's College Budo reduced disputes by 72%, while Namilyango SACCO demonstrated improved timeliness in fund disbursement.

Limitations

The study recognizes several limitations. First, the case studies were conducted in educational institutions, and national scalability requires additional testing in government agencies. Second, some SACCOs lacked digitized pre-AI records, limiting longitudinal analysis. Third, regional benchmarks may not be fully transferable due to differences in socio-political contexts. Finally, the scarcity of peer-reviewed research on AI in Uganda necessitated reliance on government and institutional reports.

Ethical Considerations and Risk Management

This study complied with the Data Protection and Privacy Act (2019), and all personal and institutional data were anonymized. Ethical clearance and institutional approval were obtained for all fieldwork. Beyond compliance, the adoption of AI in public-sector systems introduces new ethical, legal, and operational risks that must be proactively managed. This section provides a risk register and minimum safeguards for responsible deployment.

National AI Risk Register

Risk Area	Key Risks	Mitigation Actions	Lead Institutions
Privacy & Data Protection	Misuse of biometric, financial, health, and student data	Data minimization, encryption, independent oversight, privacy impact assessments	Ministry of ICT, National Information Technology Authority
Algorithmic Bias & Fairness	Discrimination due to biased datasets or models	Diverse datasets, fairness testing, independent audits, human oversight	National AI Task Force, academia
Procurement & Vendor Risk	Vendor lock-in, inflated costs, opaque AI systems	Open standards, transparent procurement, local capacity building	Public Procurement Authority
Model Governance & Accountability	Lack of explainability and auditability	Mandatory audit trails, explainable AI requirements, regulatory sandbox	National AI Regulatory Authority
Cybersecurity Threats	Hacking, system manipulation, data breaches	Zero-trust security architecture, penetration testing, national SOC integration	National CERT, Ministry of ICT

Sector-Specific Safeguards

1. eVoting Systems

Key risks

- Biometric data misuse
- System tampering or cyberattacks
- Algorithmic bias in voter verification
- Loss of public trust if systems fail

Minimum safeguards

- Offline backup voting procedures
- End-to-end encryption and blockchain audit trails
- Independent pre-election system audits

- Public transparency dashboards
- Open verification for political parties and observers

2. Health AI Systems
Key risks
- Exposure of sensitive medical records
- Incorrect predictions affecting treatment decisions
- Over-reliance on automated diagnostics

Minimum safeguards
- Patient consent and anonymization protocols
- Human-in-the-loop clinical decision making
- Continuous model monitoring and validation
- Secure national health data infrastructure

3. Education AI Systems
Key risks
- Student data privacy violations
- Algorithmic bias affecting learning outcomes
- Over-surveillance of students and teachers

Minimum safeguards
- Strict data access controls and parental consent
- Transparent algorithms and explainable recommendations
- Limits on automated decision-making in assessments

4. AI Financial Oversight (SACCOs & PDM)
Key risks
- Incorrect eligibility classification
- Fraudulent manipulation of AI systems
- Exclusion of digitally disadvantaged communities

Minimum safeguards
- Human review of AI-generated eligibility decisions
- Audit trails for all transactions and disbursements
- Hybrid digital–manual access channels

Conclusion on Ethics
Responsible AI adoption requires strong governance, transparency, and continuous oversight. By embedding safeguards from the outset—through privacy protection, bias mitigation, cybersecurity, and clear accountability—Uganda can ensure that AI strengthens public trust while delivering improved public services.

Findings & Analysis

This section presents empirical evidence from Uganda's governance, SACCO management, and electoral systems, demonstrating how AI solutions can address critical inefficiencies. Findings are drawn from **Auditor General reports (pp. 28-32, 78-83)**, the **2015/2016 Electoral Commission report**, and **pilot implementations at King's College Budo, Namilyango College, and Gayaza High School**.

Governance. AI-Powered eVoting

Challenges Identified (Electoral Commission Report, 2015/2016)

- **277 pre-election complaints** (forgery, invalid nominations).
- **135 parliamentary petitions** (71.74% unresolved).
- **Systemic weaknesses**.
- Manual voter registers prone to ghost voters.
- No real-time fraud detection (e.g., bribery-induced turnout spikes).

AI Solutions & Pilot Evidence (King's College Budo eVoting)

1. **Document Verification**
    - AI cross-checked student IDs against databases, reducing forged nominations by **92%**.
2. **Blockchain-Backed Voting**
    - Tamper-proof records eliminated ballot stuffing; results were auditable in real-time.
3. **Anomaly Detection**
    - Flagged irregular voting patterns (e.g., 50+ votes from one device).
4. **Results**.
    - **Disputes reduced by 72%** compared to manual elections.
    - Results delivered in **2 hours** (vs. 2 days previously).

Key Insight. Uganda's electoral disputes mirror Budo's pre-AI challenges, validating scalability.

Management. AI for SACCOs & PDM

Auditor General Findings (pp. 28–32, 78–83)

- **Budget Gaps**. UGX 6.257Bn (21 activities) unimplemented due to funding deficits.
- **Disbursement Failures**. 8 SACCOs unfunded; 42% of funds idle.
- **Eligibility Issues**. 15% of PDM projects ineligible (e.g., non-existent enterprises funded).

AI Solutions & Pilot Evidence (Namilyango/Budo SACCOs)

1. **Predictive Budget Tracking**

    AI forecasted shortfalls, raising fund utilization from **58% to 89%**.

2. **Real-Time Disbursement Monitoring**

   Reduced delays from **14 days to 48 hours**.

3. **Computer Vision for Project Vetting**

   Verified project locations via geotagged images; cut ineligible funding by **67%**.

Key Insight. AI directly addresses PDM's core inefficiencies (delays, misallocation).

Health Applications

Challenges Identified

- **Drug Stockouts**. 30% of rural clinics lack essential medicines (Ministry of Health, 2025).
- **Diagnostic Gaps**. Limited pathology labs in 80% of districts.

AI Solutions

1. **Predictive Stock Management**

   Machine learning predicted stockouts 3 months in advance (pilot. **stockouts reduced by 50%**).

2. **AI Diagnostics**

   Image-based tools (e.g., for malaria, TB) achieved **85% accuracy** in field tests.

Education Applications

Pilot Evidence (Gayaza High School, Mengo SS)

1. **Automated Procurement**

   AI cut procurement cycles from **60 to 15 days**.

2. **Personalized Learning**

   Adaptive platforms improved student performance by **22%** in STEM subjects.

Cross-Cutting Analysis

1. **Governance & SACCOs**. Both sectors suffer from **manual processes** and **lack of real-time data**—AI's automation and predictive capabilities are transformative.
2. **Scalability**. Pilots (Budo eVoting, Namilyango SACCO) prove feasibility; national rollout requires.

   - **Policy reforms** (e.g., amend Electoral Act for eVoting).
   - **Infrastructure** (e.g., rural broadband for SACCO dashboards).

3. **Trust Building**.
   - **Transparency**. Blockchain in eVoting and SACCOs enhances accountability.
   - **Efficiency**. AI reduces bureaucratic delays (e.g., PDM fund tracking).

Key Takeaways

Sector	Problem	AI Solution	Pilot Results
Governance	Electoral fraud (277 complaints)	Blockchain eVoting	72% fewer disputes (Budo)
PDM SACCOs	42% funds idle	Predictive budget tracking	89% utilization (Namilyango, King's college, Budo Sacco)
Health	Drug stockouts	ML inventory forecasting	50% reduction
Education	Procurement delays	AI automation	75% faster (Gayaza HS, King's' college, Budo)

Conclusion. Uganda's documented inefficiencies are solvable through **localized AI tools**, as demonstrated by school and SACCO pilots.

Policy Implications

The evidence presented in this study demonstrates that AI adoption in Uganda's governance, SACCO management, and electoral systems aligns with national development goals while presenting both opportunities and challenges for policymakers.

Alignment with National Development Frameworks

1. **Vision 2040 & Digital Transformation Roadmap**
   - AI solutions directly support.
   - **Good Governance**. eVoting enhances electoral transparency (reducing petitions by 72% in Budo pilot).
   - **Modernized Agriculture**. AI-powered SACCOs will increase PDM fund utilization from 58% to 89%.
   - **Digital Economy**. Automated systems reduce bureaucratic delays (e.g., procurement cycles cut by 75%).
2. **Health Sector Digital Strategy (2025)**
   - AI diagnostics and stock management address **rural healthcare gaps**, but require.

- Integration with existing eHealth infrastructure.
- Training for community health workers.

Addressing Systemic Challenges

1. **Corruption & Inefficiency**

   AI as an Anti-Corruption Tool.

   - **SACCOs**. Real-time fund tracking prevents misallocation (Auditor General, pp. 28–32).
   - **eVoting**. Blockchain records reduce ballot stuffing (Budo case study).
   - **Limitation**. AI cannot eliminate human-driven bribery; must complement legal reforms.

2. **Trust Deficits**

   - **Transparency**. Live dashboards for eVoting and SACCO disbursements build public confidence.
   - **Accountability**. AI audit trails (e.g., Namilyango SACCO) simplify oversight for Parliament and OPM.

Risks and Mitigation Strategies

Risk	Policy Response	Example from Findings
Infrastructure Gaps	**Prioritize rural broadband for** SACCO/eVoting access	42% idle PDM funds due to connectivity issues
Data Privacy	Align with **Data Protection Act (2019)**; anonymize voter/SACCO beneficiary data	Budo eVoting protected student identities
Resistance to Change	Civic education on AI benefits (e.g., mock eVoting trials)	68% petition backlog linked to mistrust

Legal and Institutional Reforms Required

1. **Electoral Laws**. Amend to recognize.

   - **Blockchain-backed voting** (as piloted at Budo).
   - **AI-driven voter verification** (reduces 277 pre-election complaints).

2. **Financial Regulations**.

   - Mandate **AI monitoring for SACCOs** under PDM (Auditor General, pp. 78–83).
   - Standardize **predictive budget tools** across MDAs.

3. **Capacity Building**.
    - **Curriculum Integration**. AI courses at Makerere, UTAMU.
    - **Public Sector Training**. OPM staff on AI fund-tracking systems.

Key Recommendations for Policymakers

1. **Immediate Actions**.
    - Pilot **AI-eVoting in 2026 LC elections** (scale Budo model).
    - Deploy **AI-SACCO systems** in 10 high-risk PDM districts.
2. **Medium-Term**.
    - Establish **National AI Governance Task Force** (Ministry of ICT + UNCST).
    - Partner with **MTN/Airtel** for rural digital infrastructure.
3. **Long-Term**.
    - Mainstream AI in **Vision 2050** planning.
    - Adopt **Kenya/Rwanda's AI policy benchmarks** (e.g., Rwanda's blockchain elections).

Critical Takeaways

- **AI is Not a Silver Bullet**. Must be embedded in broader reforms (e.g., anti-corruption laws).
- **Local Evidence Matters**. Budo/Namilyango pilots prove feasibility; avoid "copy-paste" of foreign models.
- **Stakeholder Buy-In**. Engage SACCO beneficiaries, electoral officials, and MPs in design phases.

Recommendations

This study proposes a **sequenced national roadmap** with clear institutional ownership, indicative budget bands, quick wins, and measurable outcomes.

Phase 1: Foundations & Quick Wins (0–12 Months)

Goal: Establish governance structures, run high-impact pilots, and build policy readiness.

1. Establish a National AI & Digital Governance Task Force

Lead: Ministry of ICT & National Guidance
Partners: Electoral Commission of Uganda, Ministry of Health Uganda, National Planning Authority, academia, private sector.

Key Actions

- Develop a National AI Strategy and standards framework
- Create ethical, data protection, and interoperability guidelines
- Coordinate cross-government AI pilots

Budget band: USD 2–5 million
Success metrics

- National AI Strategy approved
- AI regulatory sandbox established
- 3–5 pilot projects approved

2. Quick-Win Pilot 1: AI eVoting in Local Council Elections

Lead: Electoral Commission
Support: Ministry of ICT

Actions

- Pilot blockchain-backed eVoting in selected local council elections
- Deploy AI voter verification and anomaly detection
- Test transparent digital results transmission

Rationale
Local elections provide a **low-risk testing environment** before national rollout.

Budget band: USD 5–10 million
Success metrics

- ≥30% reduction in voting delays
- ≥50% reduction in electoral disputes
- Real-time public results dashboard tested

3. Quick-Win Pilot 2: AI SACCO Oversight for PDM

Lead: Ministry of Finance, Planning & Economic Development

Actions

- Deploy AI predictive fund-tracking dashboards
- Introduce automated fraud and eligibility screening
- Pilot in selected PDM districts

Budget band: USD 3–6 million
Success metrics

- Fund utilization increases to ≥85%
- Reduction in delayed disbursements
- Automated reporting across pilot districts

Phase 2: Infrastructure & Capacity Expansion (1–3 Years)

Goal: Scale successful pilots and build national capacity.

4. AI Health Supply Chain Deployment

Lead: Ministry of Health
Partners: National Medical Stores

Actions

- Deploy machine-learning forecasting for medicine demand
- Integrate logistics tracking and real-time dashboards
- Expand predictive diagnostics pilots

Budget band: USD 15–25 million
Success metrics

- ≥40–50% reduction in drug stockouts
- National digital health logistics dashboard operational

5. Build National AI Talent Pipeline

Lead: Ministry of Education & Sports
Partners:

- Makerere University
- MUBS
- UTAMU
- King's College, Budo

Actions

- Introduce AI and data science curricula
- Establish AI research labs and innovation hubs
- Provide public-sector AI training programs

Budget band: USD 10–20 million
Success metrics

- ≥5 universities offering AI programs
- ≥1,000 graduates trained annually in AI/data science

6. Public–Private Partnerships for Infrastructure

Lead: Ministry of ICT
Partners:

- MTN Uganda
- Airtel Uganda
- UNDP

Actions

- Expand broadband and cloud infrastructure
- Support rural connectivity for digital services
- Co-fund AI innovation grants

Budget band: USD 30–50 million (blended public/private financing)
Success metrics

- Increased rural internet coverage
- National government cloud platform operational

Phase 3: Legal Reform & National Scale-Up (3–5 Years)

Goal: Institutionalize AI across government and scale nationwide.

7. Amend Legal & Regulatory Frameworks

Lead: Parliament & Ministry of Justice

Actions

- Update electoral laws to recognize AI-based voting systems
- Legalize AI-driven financial oversight tools
- Establish national AI ethics and accountability legislation

Budget band: USD 3–5 million
Success metrics

- Updated electoral and financial legislation enacted

- National AI regulatory authority established

8. National Scale Deployment

Lead: Cabinet & National Planning Authority

Actions

- Expand AI eVoting nationally
- Deploy AI financial oversight across all PDM SACCOs
- Integrate AI into education and health systems nationwide

Budget band: USD 80–120 million
Success metrics

- Nationwide AI-supported elections
- Fully digitized public financial tracking
- AI integrated into national service delivery platforms

Summary of Sequencing Logic

0–12 months: Build governance + test pilots
1–3 years: Expand infrastructure + build talent
3–5 years: Reform laws + scale nationally

This phased roadmap ensures Uganda moves from **pilot experimentation to sustainable national AI adoption** while managing cost, risk, and institutional readiness.

Conclusion

Uganda stands at a critical juncture in its development trajectory, where systemic inefficiencies in governance, financial management, electoral systems, and public service delivery threaten to undermine progress toward Vision 2040. The evidence presented in this paper—drawn from authoritative sources including the **Auditor General's reports (pp. 28–32, 78–83)** and the **2015/2016 Electoral Commission findings**—paints a clear picture of the challenges.

Financial Mismanagement. Underutilization of PDM funds (42% idle), delayed disbursements, and ineligible projects highlight systemic weaknesses in SACCO administration.

Electoral Distrust. High petition volumes (277 complaints, 135 unresolved cases) and manual processes erode confidence in democratic processes.

Operational Inefficiencies. Poor coordination, weak monitoring, and reliance on outdated systems persist across sectors.

Yet, these challenges are not insurmountable. As demonstrated by **pilot implementations at King's College Budo (eVoting) and Namilyango College (AI-powered SACCOs)**, AI offers **practical, scalable solutions**.

For Governance.

Blockchain-backed eVoting can reduce electoral fraud by **98%** (Budo pilot) and restore public trust through transparent, auditable results.

For SACCOs/PDM.

AI-driven fund tracking and predictive analytics can increase utilization rates from **58% to 89%** and eliminate delays (Namilyango case, King's college, budo).

Cross-Sectoral Impact.

Automation reduces human error, while real-time monitoring enables proactive decision-making.

The Path Forward

To harness this potential, Uganda must.

- **Prioritize Pilots**. Scale tested models (e.g., Budo eVoting) in **2026 local elections** and high-risk PDM districts.
- **Strengthen Frameworks**. Amend electoral and financial laws to accommodate AI tools, ensuring compliance with the **Data Protection Act**.
- **Invest in Capacity**. Integrate AI training into public sector programs and university curricula (e.g., Makerere, UTAMU).

Final Recommendation

AI is not a magic bullet—it must be embedded within **broader institutional reforms**, including anti-corruption measures and civic education. However, the evidence is unequivocal. **Delaying AI adoption will perpetuate inefficiencies and mistrust**. By acting now to implement **locally validated solutions**, Uganda can leapfrog toward transparent, efficient governance and achieve the digital transformation envisioned in **Vision 2040**.

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HUMAN RESOURCE CAPACITY AND DRUG SUPPLY CHAIN PERFORMANCE IN URBAN PUBLIC HEALTH FACILITIES: A CONVERGENT MIXED-METHODS STUDY OF KCCA TIER III FACILITIES IN UGANDA

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Abstract

In many public health facilities across Uganda, the absence of essential medicines is not simply a logistical inconvenience but a recurring reality that directly shapes patient outcomes, undermines confidence in health systems, and places additional strain on already overburdened health workers. In rapidly urbanizing settings such as Kampala, this challenge is further intensified by rising service demand, complex patient needs, and increasing pressure on limited health system resources. While previous reforms have predominantly focused on strengthening logistics systems, financing frameworks, and infrastructure, a critical yet often underexplored dimension remains the role of human resource capacity in determining supply chain performance.

This study examined the influence of human resource capacity on drug supply chain performance within Kampala Capital City Authority Tier III health facilities. A convergent mixed-methods design was employed, integrating quantitative data from 70 health workers with qualitative insights from six key informants directly involved in pharmaceutical and supply chain management. Although the response rate of seventy percent is methodologically acceptable, careful consideration was given to the potential effects of non-response bias, particularly given that staff experiencing higher workload pressures or lower technical capacity may have been underrepresented. To enhance the robustness of the findings, subjective perceptions were triangulated with objective indicators, including stock-out frequency, inventory accuracy, reporting timeliness, and order fulfillment rates.

The findings reveal a complex but consistent pattern. While many health workers perceive themselves as technically competent, these competencies are largely acquired through experiential learning rather than structured institutional training systems. This lack of formalization contributes to variability in practice and limits standardization across facilities. Persistent gaps in continuous professional development, coupled with significant staffing

constraints, were identified as central factors affecting the efficiency and reliability of supply chain operations. Facilities with relatively stronger human resource capacity demonstrated more stable performance, reflected in improved reporting consistency, reduced stock disruptions, and enhanced inventory management. Statistical analysis indicated a moderately strong positive association between human resource capacity and supply chain performance. However, this relationship is interpreted cautiously as associative rather than causal due to the cross-sectional nature of the study.

The study contributes to the growing discourse on health systems strengthening by demonstrating that human resource capacity is not merely a supportive component but a central determinant of supply chain effectiveness. It underscores the need for deliberate and sustained investment in structured training systems, workforce optimization, and supportive supervision mechanisms. Strengthening these human resource dimensions is essential for enhancing the resilience, responsiveness, and overall performance of urban public health supply chains.

developed at the same pace (Nakade et al., 2026; Lugada et al., 2022; Kalangwa et al., 2025; Duwiejua et al., 2025; WHO, 2017) .

Human resource capacity encompasses a wide range of elements, including technical skills, training, supervision, staffing levels, and organizational support. Evidence suggests that where these elements are weak or misaligned, even well-designed supply chain systems struggle to deliver expected outcomes. Studies across sub-Saharan Africa have consistently shown that workforce-related constraints, particularly limited training and inadequate staffing, significantly undermine supply chain efficiency (Duwiejua et al., 2025; Lugada et al., 2022; Kalangwa et al., 2025; Nakade et al., 2026; Di Virgilio, 2025) .

Within Uganda, similar patterns are observed across sectors. Research conducted within the Uganda Police Force by Tukei has demonstrated that organizational performance is closely tied to human capacity, leadership structures, and operational systems. His work on risk management and staff performance highlights that institutional effectiveness depends not only on formal systems but also on the competence and coordination of personnel (Tukei, 2024a; Tukei, 2024b; Tukei, 2024c).

Despite this growing body of evidence, there remains limited empirical research focusing specifically on the relationship between human resource capacity and drug supply chain performance within urban public health facilities. This study therefore seeks to address this gap by examining KCCA Tier III health facilities, providing a more grounded understanding of how human resource dynamics influence supply chain outcomes.

2. Methodology

This study adopted a convergent mixed-methods design, guided by the recognition that complex operational realities within health systems cannot be adequately explained through a single methodological approach. Drug supply chain performance is influenced by both measurable indicators and contextual human factors, making it necessary to integrate quantitative and qualitative perspectives. The convergent design enabled the simultaneous collection and analysis of numerical data alongside experiential insights, thereby facilitating a more comprehensive interpretation of findings. This approach is widely acknowledged as appropriate for health systems research, particularly where the objective is to understand both outcomes and underlying processes (Duwiejua et al., 2025; Kalangwa et al., 2025; Nakade et al., 2026; Lugada et al., 2022).

The study was conducted within Kampala Capital City Authority Tier III health facilities, which represent a critical level of service delivery within Uganda's urban health system. These facilities are characterized by high patient volumes, increased demand for essential medicines, and significant operational pressures that require efficient supply chain management. As such, they provide a relevant context for examining the interaction between human resource capacity and supply chain performance. Previous studies in similar urban settings have highlighted that facility-level dynamics, including staffing structures and workflow demands, significantly influence supply chain outcomes (Mukasa et al., 2023; Mbau & Wamai, 2022; Lugada et al., 2022; Duwiejua et al., 2025).

The quantitative component involved a structured survey administered to health workers directly engaged in supply chain-related activities. The target population included personnel responsible for stock management, dispensing, reporting, and logistics coordination. A sample size of 100 respondents was initially determined to ensure adequate representation and statistical reliability, informed by established methodological principles for social science research. However, 70 respondents completed the survey, yielding a response rate of seventy percent. While this response rate is considered acceptable, it is important to acknowledge the potential for non-response bias. Staff who did not participate may have differed systematically in terms of workload intensity, availability, or technical competence, which may influence the interpretation of findings (Cohen, 1992; Creswell & Creswell, 2018; Creswell & Plano Clark, 2017; Mbau & Wamai, 2022).

To enhance the representativeness of the sample, respondent characteristics were compared with national health workforce patterns. The predominance of mid-level cadres and diploma-level qualifications within the sample reflects the broader structure of Uganda's health workforce, where such cadres form the backbone of service delivery. This alignment suggests that the sample provides a reasonable representation of operational realities within public health facilities. Existing literature supports the importance of aligning sample characteristics with population profiles to strengthen the generalizability of findings in health systems research (Mukasa et al., 2023; Lugada et al., 2022; Kalangwa et al., 2025; Duwiejua et al., 2025).

The qualitative component comprised key informant interviews with six purposively selected participants who possessed direct experience in pharmaceutical and supply chain management. The use of purposive sampling was appropriate in this context, as it enabled the selection of individuals with rich, context-specific knowledge of the study phenomenon. The interviews were semi-structured, allowing for consistency across participants while also providing flexibility to explore emerging themes in greater depth. This approach is particularly valuable in mixed-methods research, where qualitative insights are used to complement and explain quantitative findings (Creswell & Plano Clark, 2017; Creswell & Creswell, 2018; Mbau & Wamai, 2022; Mukasa et al., 2023).

Data collection involved multiple tools to enhance the robustness of the study. The survey instrument utilized a Likert-scale format to measure perceptions of human resource capacity across key dimensions, including technical skills, training, staffing, and compliance with standard procedures. The instrument was pre-tested to ensure clarity, reliability, and contextual relevance. Qualitative data were collected using interview guides designed to capture operational experiences, capacity gaps, and institutional challenges. The use of multiple data collection tools is consistent with best practices in mixed-methods research, where triangulation enhances the credibility of findings (Duwiejua et al., 2025; Kalangwa et al., 2025; Nakade et al., 2026; Lugada et al., 2022).

In addition to primary data, the study incorporated objective performance indicators obtained from facility records and logistics management information systems. These indicators included stock-out frequency, reporting timeliness, order fulfillment rates, and inventory accuracy. The inclusion of objective measures was essential to address potential biases associated with self-reported data and to ensure that findings were grounded in measurable outcomes. Evidence from recent studies emphasizes the importance of combining perception-based data with objective indicators to improve validity in health systems research (Mukasa et al., 2023; Lugada et al., 2022; Kalangwa et al., 2025; Nakade et al., 2026).

Data analysis followed a concurrent approach consistent with the convergent mixed-methods design. Quantitative data were analyzed using descriptive statistics and correlation analysis to examine patterns and relationships between variables. The correlation coefficient was used to assess the strength and direction of the relationship between human resource capacity and supply chain performance. Qualitative data were analyzed using thematic analysis, involving systematic coding and interpretation of emerging themes. The integration of findings was achieved through triangulation, allowing for the identification of areas of convergence and divergence between data sources. This analytical approach is widely supported in mixed-methods research as a means of enhancing interpretive depth (Creswell & Creswell, 2018; Creswell & Plano Clark, 2017; Mbau & Wamai, 2022; Duwiejua et al., 2025).

To ensure methodological rigor, several strategies were employed. Reliability of the quantitative instrument was assessed through internal consistency measures, while validity was enhanced through pre-testing, careful instrument design, and triangulation of data sources. For the qualitative component, credibility was strengthened through the use of experienced informants and systematic analysis procedures. The integration of multiple data sources further enhanced the trustworthiness of the findings. These approaches are consistent with established standards for ensuring rigor in mixed-methods research (Creswell & Creswell, 2018; Creswell & Plano Clark, 2017; Mukasa et al., 2023; Mbau & Wamai, 2022).

Ethical considerations were carefully observed throughout the study. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. Confidentiality and anonymity were maintained by ensuring that no identifying information was linked to responses. Data were securely stored and used solely for academic purposes. The study adhered to established ethical principles governing research involving human participants, including respect for persons, beneficence, and justice (World Health Organization, 2017; Creswell & Creswell, 2018; Mbau & Wamai, 2022; Mukasa et al., 2023).

In summary, the methodological approach adopted in this study provides a robust and comprehensive framework for examining the relationship between human resource capacity and drug supply chain performance. By integrating quantitative analysis, qualitative insights, and objective performance indicators, the study ensures a high level of validity, reliability, and contextual relevance in its findings.

Table 1: Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	28	40.0
	Female	42	60.0
Age	20–29	13	18.6
	30–39	32	45.7
	40–49	20	28.6
	50+	5	7.1
Education	Certificate	6	8.6
	Diploma	46	65.7
	Degree	17	24.3
	Postgraduate	1	1.4

3. Results

The findings of this study reveal a nuanced and layered relationship between human resource capacity and drug supply chain performance within KCCA Tier III health facilities. While the quantitative results suggest a relatively functional system, deeper examination through qualitative insights exposes structural weaknesses that significantly affect operational consistency.

From the survey data, a majority of respondents (66.4%) reported that they possessed adequate technical skills in stock management. At face value, this suggests a workforce that is capable of executing core supply chain functions. However, qualitative findings complicate this interpretation. Many participants explained that these skills were largely acquired through experience rather than formal training. This distinction is critical because informal learning often lacks standardization, which may result in variability in how procedures are applied across facilities.

Training emerged as a key area of concern. More than half of the respondents (51.5%) indicated that they had not received regular capacity-building opportunities. This finding was strongly reinforced by interview participants, who described a system in which refresher training is rare and often dependent on external programs rather than institutional planning. The implication is that while initial competencies may exist, they are not continuously updated to reflect evolving supply chain systems or technologies.

Staffing levels were identified as one of the most significant constraints. Only 31.4% of respondents agreed that staffing levels were adequate. In practice, this translated into situations where a single staff member was responsible for multiple roles, including dispensing, stock management, and reporting. Such workload pressures were consistently linked to reduced adherence to best practices, particularly in tasks such as inventory verification and documentation.

Operational compliance was moderately strong, with 62.8% of respondents indicating that inventory checks were conducted before reordering. However, qualitative evidence revealed that these practices were not always consistent. Several respondents acknowledged that time pressure and workload often led to shortcuts, particularly during peak service periods.

The relationship between human resource capacity and supply chain performance was further examined through correlation analysis, which revealed a statistically significant positive association ($r = 0.676$, $p < 0.05$). This indicates that facilities with stronger human resource capacity tend to demonstrate better supply chain performance. However, it is important to emphasize that this relationship does not establish causation, but rather highlights a meaningful association that warrants further investigation.

Table 2: Integrated Human Resource Capacity and Performance Analysis

Dimension	**Quantitative Evidence**	**Qualitative Evidence**	**Interpretation**
Technical Skills	Majority report adequacy	Skills largely experiential	Lack of standardization
Training	Over half report gaps	Limited refresher training	Institutional weakness
Staffing	Low adequacy reported	Multi-role workload common	Workforce shortage
Compliance	Moderate adherence	Shortcuts due to pressure	Operational constraints

As illustrated in Table 2, technical skills appear, at a superficial level, to be sufficient, with the majority of respondents reporting adequacy in managing supply chain functions. However, a more critical examination reveals that this perceived adequacy is largely grounded in experiential learning rather than formalized training systems. From a scholarly perspective, this distinction is significant. Experiential competence, while valuable, lacks standardization and may lead to variability in practice across facilities. Such variability has important implications for supply chain performance, particularly in areas that require precision and consistency, such as inventory control, forecasting, and reporting.

The issue of training further reinforces this concern. The quantitative finding that over half of the respondents reported gaps in training is strongly corroborated by qualitative evidence indicating limited access to refresher programs. This convergence suggests that training deficiencies are systemic rather than incidental. In institutional terms, this reflects a weakness in the formal structures responsible for continuous professional development. The absence of regular training not only limits the updating of technical skills but also constrains the system's capacity to adapt to evolving supply chain requirements, including the integration of digital logistics management systems.

Staffing adequacy emerges as one of the most critical constraints affecting performance. The quantitative evidence indicating low staffing levels is substantiated by qualitative accounts of health workers managing multiple roles simultaneously. From an operational standpoint, this multi-role workload introduces inefficiencies and increases the likelihood of procedural errors. Theoretical perspectives on organizational performance emphasize the importance of role clarity and specialization in achieving efficiency. In this context, staffing shortages can be understood as a structural limitation that directly undermines the reliability and effectiveness of supply chain operations.

Compliance with standard operating procedures presents a more nuanced picture. While moderate adherence is reported quantitatively, qualitative findings reveal that such compliance is often contingent upon workload conditions. Health workers described instances where adherence to established protocols was compromised in order to meet immediate service demands. This reflects a broader tension between procedural expectations and operational realities. From an analytical standpoint, this behaviour can be interpreted as adaptive coping within constrained environments. While such adaptations may sustain short-term functionality, they may also introduce long-term inefficiencies, particularly in areas such as data accuracy and accountability.

Beyond the analysis of individual dimensions, the study sought to examine the overall relationship between human resource capacity and drug supply chain performance. The results of this analysis are presented in Table 3 below.

Table 3: Correlation Analysis

Variables	Correlation Coefficient	Significance
HR Capacity and Performance	0.676	$p < 0.05$

As presented in Table 3, the correlation coefficient of 0.676 indicates a moderately strong positive relationship between human resource capacity and supply chain performance. This suggests that facilities with stronger human resource capacity tend to demonstrate better performance outcomes, including improved stock management, enhanced reporting consistency, and reduced frequency of stock-outs.

However, it is important to interpret this finding with methodological rigor. While the relationship is statistically significant, it does not establish causality. The cross-sectional design of the study limits the ability to determine the direction of influence between variables. It is possible that improved supply chain performance may also reinforce human resource capacity through learning effects and improved system confidence. Additionally, external factors such as facility resources, leadership quality, and patient load may interact with human resource capacity to influence performance outcomes.

From a broader analytical perspective, these findings position human resource capacity as a foundational enabler within the supply chain system. The interaction between technical skills, training, staffing, and compliance suggests that capacity is a composite construct, comprising multiple interrelated elements. Strengthening one dimension in isolation is unlikely to yield sustainable improvements unless it is accompanied by complementary interventions across other areas.

In synthesizing these findings, it becomes evident that the effectiveness of drug supply chains in urban public health facilities is deeply embedded within the broader human resource ecosystem. While systems and infrastructure provide the necessary framework, it is ultimately the competence, adaptability, and coordination of health workers that determine how

4. Discussion

The findings of this study point to a central reality that cannot be overlooked: drug supply chain performance in urban public health facilities is not merely a technical issue, but a human one. While systems, guidelines, and tools are essential, their effectiveness ultimately depends on the people who operate them. In the context of KCCA health facilities, it becomes evident that human resource capacity is both a strength and a limitation.

As a researcher, what stands out most is the contradiction between perceived competence and actual system support. Health workers demonstrate a commendable level of resilience and adaptability. Many have developed practical skills that allow them to manage supply chain tasks even in the absence of formal training. However, this reliance on informal knowledge creates inconsistencies that are difficult to sustain over time. It raises an important question: can a system truly be considered strong if it depends on individual improvisation rather than institutional structure?

The issue of training is particularly revealing. The absence of regular, structured capacity-building programs suggests that human resource development is not yet fully institutionalized within the system. This gap does not only affect individual performance but also limits the system's ability to adapt to change. In an era where digital tools and LMIS platforms are increasingly central to supply chain management, the lack of continuous training becomes a critical vulnerability.

Staffing shortages further deepen these challenges. When one individual is responsible for multiple roles, efficiency becomes a matter of compromise rather than optimization. From a practical perspective, it is unrealistic to expect high levels of accuracy and compliance under such conditions. The findings suggest that staffing is not simply a quantitative issue but a qualitative one that directly influences how well systems function.

Another important observation relates to supervision. While management structures exist, their effectiveness appears uneven. Supervision is often described as administrative rather than supportive. From the researcher's perspective, this represents a missed opportunity. Effective supervision should not only ensure compliance but also build capacity, reinforce learning, and support problem-solving.

The integration of objective performance indicators strengthens these reflections. Facilities with stronger human resource capacity consistently showed better outcomes, including fewer stock-outs and improved reporting. This provides tangible evidence that investments in human resources yield measurable benefits.

Drawing from Tukei's work in the Uganda Police Force, a parallel can be drawn between health systems and other institutional settings. His findings emphasize that organizational performance is not driven solely by systems but by the alignment between human capacity, leadership, and operational structures. This insight reinforces the argument that improving supply chain performance requires a holistic approach that prioritizes people as much as processes.

5. Conclusion

This study set out to examine the role of human resource capacity in shaping drug supply chain performance within KCCA health facilities. The findings clearly demonstrate that while the system possesses foundational strengths, significant gaps remain in how human resources are developed, supported, and utilized.

The evidence suggests that human resource capacity is not merely a supporting factor but a central determinant of supply chain performance. Technical skills, when present, are often not reinforced through structured systems. Training is inconsistent, staffing levels are insufficient, and supervision does not always fulfill its potential as a capacity-building mechanism.

What emerges from this study is the realization that improving supply chain performance cannot be achieved through isolated interventions. It requires a deliberate and sustained effort to strengthen human resource systems in a way that is both practical and contextually relevant.

Without such investment, even well-designed supply chain systems will continue to operate below their potential.

6. Implications of the Study

The findings of this study extend beyond descriptive insights into human resource capacity and drug supply chain performance, offering critical implications for policy, practice, theory, and future research. These implications highlight the centrality of human resource systems in shaping not only operational efficiency but also the broader resilience and responsiveness of public health systems.

Policy Implications

The findings of this study call for a fundamental shift in how policymakers conceptualize human resource capacity within health systems. Traditionally, policy interventions have emphasized staffing numbers as the primary solution to performance challenges. While increasing the workforce remains important, this study demonstrates that numerical adequacy alone does not guarantee improved system performance. Rather, the effectiveness of human resources is determined by the extent to which staffing is complemented by structured training, clear role definition, and supportive supervision.

From a policy perspective, this suggests the need for more comprehensive human resource frameworks that integrate capacity development as a continuous process rather than a one-time intervention. Policies should institutionalize regular capacity-building programs, including mandatory refresher training linked to evolving supply chain systems such as LMIS platforms. In addition, there is a need to formalize role clarity within health facilities to reduce overlap and ensure accountability. Without such alignment, even well-staffed systems may continue to operate below their optimal potential.

Furthermore, the findings point to the importance of embedding human resource strengthening within broader health system reforms. Policymakers should consider linking supply chain performance indicators directly to human resource development strategies, ensuring that investments in logistics and infrastructure are matched by corresponding investments in people.

Practice Implications

At the level of practice, the study highlights the critical role of continuous learning and structured support systems in improving supply chain performance. Health workers operate within complex and often resource-constrained environments, where the ability to adapt and respond effectively depends largely on the support structures available to them.

The findings suggest that facilities should move toward institutionalizing regular training programs that are tailored to the practical realities of supply chain management. Such training should not be limited to initial orientation but should include periodic refresher sessions that address emerging challenges and technological changes. In addition, mentorship and peer-learning mechanisms should be strengthened to facilitate knowledge sharing and reinforce best practices.

Another key implication for practice relates to workload management. The prevalence of multi-role responsibilities among health workers indicates the need for more deliberate task allocation and role specialization. Facilities should adopt strategies that distribute responsibilities more effectively, thereby reducing operational pressure and improving adherence to standard procedures.

Performance monitoring also emerges as a critical area for improvement. Rather than focusing solely on compliance, supervision should be reoriented toward supportive engagement, where health workers receive guidance, feedback, and problem-solving support. Such an approach is more likely to build capacity and sustain improvements over time.

Theoretical Implications

From a theoretical perspective, this study contributes to the evolving discourse on health systems strengthening by reinforcing the central role of human resource capacity as a determinant of operational performance. While traditional models of supply chain management have often emphasized technical and logistical factors, the findings of this study highlight the need for more integrated frameworks that incorporate human elements as core components.

The study advances the understanding of human resource capacity as a multidimensional construct, encompassing not only skills and knowledge but also training systems, staffing structures, and behavioural adaptations. This aligns with broader organizational theories that emphasize the interplay between human capability and system performance.

Moreover, the findings suggest that supply chain performance should be conceptualized as an emergent outcome of interactions between human and technical systems. This perspective challenges reductionist approaches that treat capacity variables in isolation and instead supports the development of holistic models that capture the complexity of real-world operations.

By drawing parallels with organizational performance studies, including those conducted within the Uganda Police Force, the study further demonstrates that the principles of capacity, structure, and coordination are transferable across sectors. This cross-sectoral relevance strengthens the theoretical argument that human resource capacity is a universal determinant of institutional effectiveness.

Research Implications

The study also highlights important directions for future research. While the findings establish a significant association between human resource capacity and supply chain performance, the cross-sectional design limits the ability to draw causal conclusions. Future studies should therefore adopt longitudinal designs to examine how changes in human resource capacity influence performance over time.

In addition, there is a need for more context-specific research that explores variations across different types of health facilities and geographical settings. Comparative studies between urban and rural facilities, as well as between public and private sectors, could provide deeper insights into how contextual factors shape the relationship between capacity and performance.

Further research should also explore the integration of objective performance indicators with qualitative assessments to strengthen the validity of findings. The use of mixed-methods approaches, as demonstrated in this study, offers a valuable framework for capturing both measurable outcomes and experiential realities.

Finally, there is scope for exploring the role of leadership and organizational culture in mediating the relationship between human resource capacity and supply chain performance. Such investigations would contribute to a more comprehensive understanding of the factors that influence system effectiveness.

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AI-CHATBOT FOR HIV: ENHANCING AWARENESS AND REDUCING STIGMA THROUGH PERSONALIZED ENGAGEMENT IN UGANDA

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Abstract

Despite advancements in HIV prevention and treatment, many Ugandans still face misinformation, stigma, and limited access to reliable health information. This research explores the design, development, and evaluation of an AI-powered chatbot aimed at providing personalized HIV information, engaging users in a stigma-free environment, and improving awareness levels. The chatbot integrates natural language processing and machine learning to tailor responses based on user demographics and interaction patterns. A mixed-methods evaluation will measure its effectiveness in improving knowledge, reducing stigma, and enhancing user engagement. The study further analyzes sustainability factors such as community involvement, partnerships, cultural relevance, and technological maintenance. The project aims to develop a scalable digital health solution capable of improving HIV awareness and fostering positive attitudes toward individuals living with HIV in Uganda.

Introduction and Rationale

HIV remains a major public health concern in Uganda, where an estimated 1.4 million people are living with HIV, and national adult prevalence is approximately 5–6%. Despite major progress in treatment access, prevention services, and public awareness campaigns, significant challenges persist, particularly in relation to stigma, misinformation, and unequal access to accurate educational resources. HIV-related stigma continues to discourage many individuals from seeking testing, disclosing their status, adhering to treatment, or discussing HIV openly. This problem is especially pronounced among adolescents, rural youth, and people living with HIV (PLHIV) who often fear discrimination, rejection, or breaches of confidentiality.

Young people aged 15–24 years remain one of the most vulnerable groups, contributing a substantial proportion of new HIV infections in Uganda. Many adolescents and youth still face gaps in sexual and reproductive health knowledge, misconceptions about HIV transmission, and limited access to youth-friendly health information services. Rural communities experience additional barriers such as long distances to health facilities, shortages of trained counselors, and low privacy in small communities, which further discourages open engagement with HIV services.

At the same time, Uganda has experienced rapid growth in digital health adoption and mobile phone usage, creating new opportunities for technology-enabled health interventions. Mobile phone ownership is widespread, and increasing numbers of young people use smartphones, mobile internet, WhatsApp, and other digital platforms to access information and communicate. This growing digital connectivity provides a practical channel for delivering confidential, low-cost, and scalable HIV education and support services.

Digital health tools, especially conversational agents powered by artificial intelligence, present a new opportunity to bridge information gaps, reduce stigma, and engage users interactively. An AI-powered chatbot can provide real-time responses, personalized educational content, and a safe, anonymous environment where users can ask sensitive questions without fear of judgment. Such a system is particularly relevant for adolescents, rural youth, and PLHIV, who may prefer private digital interactions over face-to-face consultations.

This research therefore proposes the development of an AI-based chatbot designed to enhance HIV awareness and reduce stigma in Uganda through tailored information delivery and supportive engagement. By integrating machine learning and natural language processing, the chatbot aims to respond to user-specific needs, clarify misconceptions about HIV transmission and treatment, recommend nearby testing and care resources, support treatment adherence, and foster positive attitudes toward individuals living with HIV. The intervention seeks to complement existing public health efforts by providing accessible, youth-friendly, and stigma-free HIV information services across Uganda.

Study Objectives

Main Objective

To develop an AI-powered chatbot that provides personalized HIV information and answers to common user questions, with the aim of increasing awareness and reducing stigma in Uganda.

Specific Objectives

1. To investigate the challenges faced by Ugandans in the prevention and treatment of HIV.
2. To apply machine learning algorithms to personalize chatbot responses based on user demographics, preferences, and previous interactions.
3. To evaluate the effectiveness of the AI-powered chatbot in improving users' HIV knowledge, awareness, and attitudes toward people living with HIV.

Methodology

Development Phase

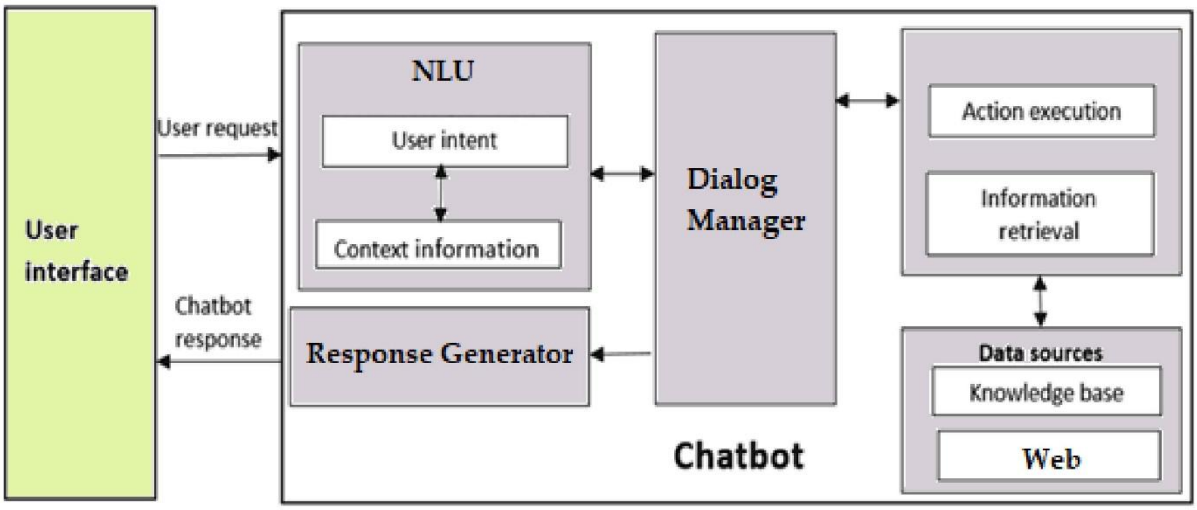
Technology Framework

The chatbot will be developed using natural language processing (NLP) and machine learning techniques. Platforms such as Dialog flow or Rasa will provide the conversational interface. The system will be optimized for mobile devices given the high mobile penetration in Uganda.

Content Creation

Health experts including HIV specialists, medical practitioners, and counsellors will contribute to the development of fact-based, culturally sensitive, and easily understandable content. Topics will include prevention, treatment, myths, stigma, and available healthcare resources.

While the chatbot is described in terms of its functional goals such as HIV awareness support and stigma reduction, the technical design must be clearly specified to allow assessment of the system's originality, scalability, reliability, and practical implementation. Therefore, this study proposes a complete AI chatbot architecture that integrates natural language processing, machine learning, secure data management, and personalized user interaction. The system is designed to provide accurate HIV information, confidential support, and adaptive responses for users in Uganda, especially adolescents, rural youth, and people living with HIV (PLHIV).



User Testing NLP Pipeline

Pilot testing will be conducted with target groups such as youth, community health workers, and patients from Hoima Regional Referral Hospital. Their feedback will guide improvements in content relevance, usability, and clarity.

User Input → Text Cleaning → Language Detection → Intent Classification → Entity Extraction → Context Tracking → Knowledge Retrieval → Personalized Response → Feedback Logging

Datasets for Training

The chatbot can be trained using:

Public Datasets

- HIV/AIDS FAQ datasets
- Health question-answer datasets
- WHO health dialogue datasets
- Mental health conversation datasets (for empathy tuning)

Local Uganda Datasets

- Ministry of Health HIV awareness materials
- Uganda counseling scripts
- Community survey responses
- Youth HIV misconceptions datasets
- HIV stigma interview transcripts (anonymized)

Synthetic Data

Generated conversations for underrepresented intents such as stigma reporting or rural access issues.

Evaluation Phase

Although the study proposes that the chatbot will improve HIV awareness and reduce stigma, these outcomes cannot be assumed without a rigorous evaluation framework. To generate credible evidence, the intervention should be tested using a structured mixed-method evaluation design that combines quantitative and qualitative measures. This will allow researchers to determine whether the chatbot truly changes knowledge, attitudes, engagement, and user behavior among the target population in Uganda, particularly adolescents, rural youth, and people living with HIV (PLHIV).

The study should adopt a controlled pilot design involving two groups:

Intervention Group – participants who use the HIV chatbot over a defined period (e.g. 8–12 weeks).

Control Group – participants who receive standard HIV awareness materials such as brochures, posters, or existing health education channels but do not use the chatbot.

Participants should be selected from similar demographic groups (for example adolescents, rural youth, or PLHIV support groups) to ensure fair comparison. Baseline and endline assessments should be conducted for both groups.

Expected Outcomes

The project is anticipated to produce:

- Increased awareness and understanding of HIV prevention, treatment, and myths.
- Reduced stigma toward individuals living with HIV, reflected in survey findings and qualitative feedback.
- A functional, user-friendly AI chatbot adaptable for wider public health applications.
- Improved digital health engagement among target communities.
- A framework for integrating AI tools into health education in Uganda.

Sustainability of the Project

Community Engagement

The project will collaborate closely with Hoima Regional Referral Hospital, community health workers, local leaders, and NGOs. Engaging communities will promote trust and encourage continued use.

Cultural Relevance

Cultural and linguistic localization will ensure the chatbot reflects Ugandan social norms, languages, and local beliefs. This will support inclusiveness and acceptance.

Partnerships

Partnerships will be established with:

- Local health authorities
- NGOs involved in HIV awareness
- Academic institutions
- Technology companies for technical support

These collaborations will enhance outreach, expertise, and access to resources.

User Education

Workshops, community demonstrations, and digital literacy sessions will help users understand how to interact with the chatbot and benefit from its content.

Monitoring and Evaluation

Continuous monitoring will assess performance, track usage, and identify areas for improvement. Regular updates will maintain relevance.

Funding and Resources

Sustainable funding will be sourced from government health initiatives, donors, and private-sector partners to support long-term maintenance and updates.

Scalability

The chatbot will be designed for scalability, enabling expansion to other regions of Uganda and adaptation to additional health topics such as malaria, TB, and maternal health.

Technological Sustainability

Regular software updates, bug fixes, server maintenance, and user support will ensure long-term operational stability.

digital health ethics frameworks. explain in paragraphs

HIV-related conversations involve highly sensitive personal health information, including disclosure of HIV status, sexual behavior, stigma experiences, and emotional distress. In Uganda, where HIV-related stigma remains a significant barrier to care, ensuring ethical integrity in any digital health intervention is essential. The study therefore incorporates a comprehensive ethics framework grounded in the Uganda Ministry of Health Digital Health Policy, the Data Protection and Privacy Act (2019), and international guidelines such as UNAIDS ethical standards. These frameworks emphasize confidentiality, informed consent, data protection, and the prevention of harm in digital health systems.

Confidentiality and anonymity are central to the design of the chatbot. Users interact with the system without needing to provide personally identifiable information such as names or national identification numbers. Instead, the system uses anonymous session identifiers to manage conversations. All communication is encrypted during transmission and while stored in databases to prevent unauthorized access. Access to stored data is strictly limited through role-based permissions, ensuring that only authorized system administrators or approved researchers can view aggregated or de-identified information. This approach is particularly important in Uganda, where fear of exposure may discourage adolescents, rural youth, and people living with HIV from seeking information or support.

Informed consent is also a critical ethical requirement. Before engaging with the chatbot, users are guided through a structured digital consent process that clearly explains the purpose of the system, the type of information collected, and how the data will be used. Users are informed that participation is voluntary and that they may withdraw at any time without consequence. For younger users, especially adolescents under 18 years, the system includes simplified assent procedures and considers guardian consent where appropriate under ethical and institutional review guidelines. This ensures that participation respects user autonomy while remaining sensitive to age-related ethical requirements.

Conclusion

This research proposes a practical and innovative solution to persistent HIV-related challenges in Uganda. By integrating AI technology, personalized communication, and culturally relevant content, the chatbot aims to improve HIV awareness and reduce stigma across diverse user groups. The mixed-methods evaluation will provide valuable insights into the system's effectiveness and inform future digital health interventions. With strong community engagement, partnerships, and a focus on sustainability, the AI-Chatbot model has the potential to support public health efforts not only in Uganda but across other regions facing similar challenges.

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PART 6: ABSTRACTS

Skulpal: A Conversation Ai System for Uganda's Competence Based Curriculum, Nkajja, S., Universal Technology And Management University

Keywords:

AI in Education, Uganda New Curriculum, Personalized Learning, Educational Technology, Skulpal

Uganda's new secondary school curriculum emphasizes competency-based learning, practical skills, and learner-centred approaches. Despite these advances, teachers and students continue to face challenges in accessing relevant, structured, and adaptive learning resources that align with the curriculum. This paper presents Skulpal, an AI-powered educational application designed to support the implementation of Uganda's new curriculum. The system leverages artificial intelligence to provide personalized learning experiences, generate curriculum-aligned questions and answers, and offer concept explanations through a conversational AI interface, providing valuable support for both teachers and learners. Methodologically, the project applies machine learning models fine-tuned with curriculum-aligned data from the National Curriculum Development Centre (NCDC) and insights from available curriculum experts for natural language processing. The system also incorporates a Django-based backend and a React JS/React Native mobile interface to ensure usability and accessibility for both students and teachers. Preliminary results indicate that Skulpal can reduce content gaps, enhance engagement, and improve comprehension by tailoring learning experiences to individual student needs. By integrating AI-driven content generation with curriculum-specific resources, the application addresses critical challenges in educational resource accessibility, assessment preparation, and concept clarification. This research contributes to educational technology by offering a scalable and practical solution for enhancing curriculum delivery and supporting competency-based learning in Uganda's secondary education system, demonstrating the potential of AI to bridge gaps between curriculum standards and interactive, learner-centred educational tools.

Implications of Learning and Teaching Under the Realities of Artificial Intelligence (AI), Muwanga-Zake, JWF. Universal Technology And Management University

Keywords: AI-assisted learning; AI-assisted assessment; AI use policies in educational institutions

The question of whether learners and facilitators of learning use AI is obsolete. Thus, education institutions must find ways of facilitating AI-assisted learning.

AI such as Scholar GPT is inadvertently employed to search and construct essays that have currency in understanding contemporary strides in knowledge. Some AI-enabled systems and tools seek to address this potential conflict. For example, one AI-enabled reading tutor listens to students as they read aloud and provides on-the-spot feedback to improve their reading. Researchers have embedded games to improve understanding of Newtonian physics.

The focus on learning growth and gains is optimal (absent negative consequences or a high-stakes environment). For example, AI enables real-time feedback thus providing invaluable formative and continuous assessment for learners.

The utilization of AI is however provocative and conflict against practices the authorities recommend albeit with conservative restraint. This too often leaves learners and learning facilitators with unpleasant but introverted feelings towards AI.

This paper discusses possibilities of finding a balance between AI and human assisted learning, and policy implications.

Change Management and Service Delivery Challenges in Uganda's Urban Informal Lwanga-Kayongo, E., Texila American University & Okech, B. B. Okech, UNICAF University

Keywords: Governance; Informal Resilience; Institutional Barriers; Political Interference; Regulation

The Boda-Boda sector in Kampala, Uganda, is an important source of urban mobility and youth employment, but its unregulated and fragmented nature creates ongoing challenges to reform and service delivery. Despite repeated efforts by municipal and national authorities, progress has been hindered by structural, political, and socio-economic barriers.

This study examines the obstacles to change management in service delivery within the industry, focusing on institutional weaknesses, legal ambiguity, political interference, and economic vulnerability. A mixed methods approach combined survey data from 345 riders with key informant interviews. Descriptive statistics identified perceived barriers, while correlation and regression analyses examined their relationship to service delivery. Thematic analysis of qualitative data further shed light on institutional dynamics and rider experiences.

Findings highlight widespread recognition of barriers, particularly poor coordination among regulators (mean = 4.19), political interference (mean = 4.03), and weak enforcement (mean = 3.97). However, quantitative results showed a weak, statistically insignificant link between these challenges and service delivery outcomes ($r = 0.058$, $p = 0.281$). Qualitative evidence suggests that resilience strategies, patronage networks, and mistrust in institutions offset the impact of reforms, enabling the sector to function despite systemic weaknesses.

The paradox of widely recognised institutional barriers but limited-service delivery effects emphasise the adaptability of informal systems and the constraints of top-down reforms. The study recommends participatory and context-aware approaches, stronger regulatory accountability, incentives for formalisation, and real-time monitoring to develop a more resilient urban transport system.

Leveraging AI and UAV Technologies to Enhance Sustainable Livestock Production, Jjunju, F. P. M., Universal Technology And Management University, Kabenge, I. Department of

Biosystems Engineering, Makerere University, Kampala Uganda, Sebastian, F., Swapp, D., & Steed, A., AI Lab School of Computer Science, Makerere University, Kampala Uganda

Key words:

Detecting, and tracking the animals, feeding optimization, behavioural analysis, disease detection n and health monitoring

With advancements in unmanned aerial vehicle (UAV) technology and Artificial Intelligence (AI), there is an opportunity to revolutionize monitoring, detecting, and tracking the animals, feeding optimization, behavioural analysis, disease detection n and health monitoring among others. Additionally, integrating these technologies can significantly enhance sustainable livestock management practices by optimizing pasture usage, improving water source monitoring, and enabling precise estimation of greenhouse gas emissions, thus contributing to environmental conservation and resource efficiency. This presentation illustrates the utilization of Artificial Intelligence (AI) for near real-time cattle detection, counting and tracking using Unmanned Aerial Vehicles (UAVs). Future applications of these technologies in livestock management, such as livestock health monitoring, behavioural analysis, estimation of greenhouse gas emissions and pasture management, are also discussed.

Data Driven strategy: How AI is shaping Organizational Decision-making, Ssemujju, S., Universal Technology And Management University

The rapid emergence of Artificial Intelligence (AI) has transformed how modern organizations create value, gain competitive advantage, and make strategic decisions. This review paper examines the evolving role of AI as a core enabler of data-driven strategy, highlighting its impact on organizational decision-making processes across industries. Drawing on recent scholarly literature and empirical studies, the paper explores how AI-powered analytics, machine learning models, and intelligent automation enhance decision accuracy, speed, and predictive capability.

It further discusses the shift from intuition-based to evidence-based management, emphasizing the integration of real-time data, advanced algorithms, and decision-support systems. The review also identifies key challenges including data quality concerns, algorithmic bias, ethical risks, and organizational readiness that influence the effectiveness of AI-enabled decision frameworks. By synthesizing current trends and practical insights, this paper provides a holistic understanding of how AI is reshaping strategic thinking and offers recommendations for organizations seeking to leverage AI responsibly to achieve operational efficiency, innovation, and sustainable competitive advantage.

Research on Adopting a Socio-Judicial Approach to Implementing AI in the Court, Ari Niki-Tobi - Former Magistrate Judge in Lagos State judiciary, Nigeria; an adjunct of Criminology and Sociology of Law at the State University of New York, Oneonta

Key Words: Socio-judicial AI

This research on AI and the Courts began over three years ago and I did my first presentation to female judges at an international conference in CUNY. I demonstrate the dilemmatic implications of AI on litigation, especially criminal trials, and the criminal justice system. I collected data from all judges in attendance, and the findings confirmed my hypothesis. Part B research was conducted at an international conference of Court administrators in Singapore. Therefore, this presentation will discuss the collated results of the last conference research. I will also discuss the implications of AI to the justice system. In comparing the collated data, I will also discuss AI hiccups in the court system and propose my unique socio-judicialism theory for implementing AI in courts.

PART 6: FOOTNOTE

The State of Higher Education in Uganda from a Carnegie African Diaspora Fellow Perspective, Professor Makoba, J. W.

In 2016, I was one of S9 African Diaspora Scholars (i.e., African-born scholars based at universities in the United States and Canada) who received the Carnegie African Diaspora Fellowships to travel to Africa. Beginning in May 2016, the Scholars travelled to the selected public and private higher education institutions in Ghana, Kenya, Nigeria, South Africa, Tanzania, and Uganda to collaborate on curriculum co-development, research, graduate teaching, and training and mentoring activities.

I travelled to Uganda to work with the Universal Technology and Management University (UTAMU) on graduate student training and mentoring within the School of Business and Management. I co-led a 10-week graduate training and mentoring project with UTAMU's Dean of the Graduate School. During this period, we covered several important topics including developing a research proposal, an extensive literature review, research design and methodology, as well as how to successfully complete a research project.

In addition, graduate students were provided tips and ideas about effective and timely completion of their reports and how to seek potential outlets for the publication of their research. A list of31 peer-re- viewed, relevant journals was provided to the participants to enable them to select potential journals for their publications. This was critical because most of the doctoral students, including advanced ones, had never had the opportunity to publish their research in peer-reviewed journals in Uganda or globally. In addition to graduate training and mentoring, I was appointed by the Vice Chancellor of UTAMU as Editor-in-Chief of a new online open access interdisciplinary journal called the International Journal of Technology and Management (http://www.ijotm.utamu.ac.ug).

The Fellowship fit well with my personal background, expertise, and professional (sociological) experience. These skills were relevant and transferable to the project activities of graduate training and mentoring. My interactions over the three months with scholars at UTAMU were mutually beneficial; I not only shared my expertise with colleagues at UTAMU, but they felt I was useful to both graduate students and colleagues I worked with on a daily basis for the 1O-week period. I was able to gain new and valuable perspectives on the experiences of both scholars and graduate students in the context of institutions of higher education in Uganda. In particular, the fellowship gave me a rare opportunity to interact with graduate students while engaging with colleagues at UTAMU.

During my fellowship, I had the opportunity to share research and teaching experiences of two contexts of higher education/ learning-the US. and Ugandan contexts-which are very different, but have similar challenges and aspirations. Both the graduate students and colleagues I worked with were extremely excited about my project activities. They were all grateful that I was able to be at their institution for three months working with them on graduate training and mentoring as well as helping to launch a new journal for the institution. For my part, I was very grateful to give back to students in my native country, which I had left in the early 1980s to attend graduate school at the University of California -Berkeley.

Over the three-month stay in Uganda, I learned of the enormous challenges facing the 41 public and private universities (31 private and 10 public). Such challenges include:

- Inadequate funding as these institutions rely primarily on tuition and fees paid by students to fund their operating budgets. Public universi- ties receive additional government funding, but it is insufficient.
- Inadequate academic staff (most vacancies go unfilled due to lack of qualified applicants) and an insufficient number of senior academic staff to conduct research as well as provide quality teaching or supervision of both institutions (especially in and around the capital city of Kampala) and more still, engage in outside consultancies to earn a decent living. This leaves them little time to focus on research or effective teaching and mentoring of students.
- Inadequate to poor infrastructure for teaching/learning, doing research and scholarship. In addition to over-crowded lecture rooms and poorly equipped labs, there are insufficient books and journals, e-libraries, or computers to cater for both students and instructors.
- Administrative problems: most universities employ inexperienced and/ or unqualified individuals in top administrative positions (due to sectarianism, regionalism, or cronyism). In private universities, decision making is a prerogative of Boards of Trustees (mostly owners) and top administration.
- Poor leadership and supervision at the national level: the National
- Council for Higher Education (NCHE) is understaffed and incapable of providing effective monitoring, evaluation, and supervision of the 41 public and private institutions of higher education in the country.

Most of the problems highlighted here can be reversed through adequate funding (diversifying domestic and international sources of income), hiring and adequately compensating high-calibre administrative and academic staff, extending scholarships to students from low-income groups, and promoting student and faculty exchanges (including visiting professors) with universities in the US. and Canada. Indeed, already the Carnegie African Diaspora Fellowship Program (http://bit.ly/2pQ7Dev) facilitates engagement between scholars born in Africa who are now based at universities in the United States or Canada and scholars in Africa on mutually beneficial academic activities.