



Artificial Intelligence in Libya: A Scoping Review of the Current Landscape, Applications, and Challenges

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Abstract

This survey provides a comprehensive overview of the current state of artificial intelligence (AI) in Libya, synthesizing findings from academic literature, policy documents, technical reports, and sectoral case studies. We examine the national policy landscape, including the recently published National AI Strategy 2025–2030 and its alignment with international frameworks. The survey covers AI adoption across Libyan higher education, drawing on empirical studies of faculty attitudes, usage patterns, and institutional barriers. We review sectoral applications in agriculture and remote sensing, oil and gas, water resource management, cultural heritage, healthcare, and Arabic natural language processing. We also assess Libya's digital infrastructure, data readiness, human capital pipeline, and the emerging startup ecosystem. Despite significant barriers — including political instability, infrastructure deficits, a fragmented policy environment, and severe data scarcity — we find evidence of accelerating grassroots AI adoption and growing research output across multiple domains. We conclude with prioritized recommendations for researchers, policymakers, and international development partners.

Keywords: Artificial intelligence, Libya, education sector, health, state policy, challenges

1. Introduction

Libya occupies a distinctive position in the North African artificial intelligence landscape. As a country with Africa's largest proven oil reserves, a young and increasingly digitally connected population, and a decade of political fragmentation that has simultaneously damaged institutions and spurred grassroots innovation, its AI trajectory defies simple categorization. While the broader MENA region — particularly the Gulf states — has made substantial and well-documented progress in AI strategy, infrastructure, and deployment, Libya-specific research remains fragmented across disciplines and publication venues. At the continental level, the African Union's Continental AI Strategy provides an overarching framework that positions AI as a driver of inclusive and sustainable development across all member states [1], while analyses of Africa's AI governance landscape have highlighted



both progress and persistent gaps in translating continental strategy into national implementation [2], [3].

The gap between potential and actual AI deployment in Libya is striking. The country faces acute challenges that AI could help address: water scarcity intensified by climate change, conflict-related environmental degradation, an electricity grid struggling to meet demand, a healthcare system with limited diagnostic capacity, and an education sector whose infrastructure was severely damaged during the civil war. At the same time, Libyan researchers are publishing on LSTM-based electricity load forecasting [4], machine learning for groundwater prediction [5], deep learning for population modeling [6], and satellite-based environmental monitoring. Libyan university faculty are adopting large language models for research and teaching at rates comparable to their international peers, even as institutional policies lag.

This survey aims to consolidate the scattered literature into a coherent picture. In contrast to broad regional surveys of AI in the Middle East and Africa, we focus exclusively on Libya to provide the depth needed for informed policy and research decisions. We cover the national policy landscape (Section 2), AI in higher education (Section 3), sectoral applications (Section 4), digital infrastructure and data readiness (Section 5), the human capital pipeline (Section 6), challenges and future directions (Section 7), and the conclusions (Section 8).

TABLE 2. COMPARISON OF THIS SURVEY WITH PREVIOUS AI SURVEYS IN THE ARAB WORLD, AFRICA, AND THE MIDDLE EAST.

Survey (Author, Year)	Geographic scope	Sectoral focus	Method	Coverage of the AI landscape
Alzahrani, 2022 [7]	22 Arab countries	AI in education	Systematic review (3 databases, 29 studies)	Education sector only
Pouris, 2025 [8]	South Africa	Full AI field	Scientometric + content analysis	Research outputs only
Chipps et al., 2025 [9]	South Africa	Healthcare AI	JBIR scoping review (PCC framework), 35 studies	Health sector only
Ciecierski-Holmes et al., 2022 [10]	LMICs (global)	Health systems strengthening	Systematic scoping review	Health systems only
Plantinga et al., 2024 [11]	12 African countries	AI governance	Comparative policy analysis	Governance only
Al-zebin et al., 2025 [12]	Middle East	AI adoption (multi-sector)	Comprehensive review	Multi-sector but regional; no country-level depth in Libya
This survey	Libya (single country)	Multi-sector: policy + higher education + sectoral applications + digital infrastructure + human capital + startup ecosystem	Evidence synthesis (academic literature, policy documents, technical reports, sectoral case studies)	First verified Libya-only, multi-sector survey; adds national-policy analysis (National AI Strategy 2025–2030), Libyan Arabic NLP gap, and sector-specific data-scarcity findings

This survey is structured around six research questions that map directly onto the current landscape of AI in Libya:

RQ1:What national policies and institutional frameworks govern the development of artificial intelligence in Libya, and how do they align with continental and international frameworks?

RQ2:How is artificial intelligence being adopted across Libyan higher education, and what institutional, infrastructural, and pedagogical barriers limit its effective integration?

RQ3:In which sectors — agriculture and remote sensing, cultural heritage, oil and gas, water resources, and healthcare — is artificial intelligence being applied in Libya, and what do the reviewed studies indicate about methods, data, and outcomes?

RQ4:What is the state of Libya's digital infrastructure and data readiness, and how does it constrain AI research, deployment, and equitable access to AI tools across regions?

RQ5:What is the state of Libya's human capital and research ecosystem for artificial intelligence, and what gaps remain in Arabic natural language processing capacity?

RQ6:What structural and systemic challenges limit AI development in Libya, and which research and policy priorities do the authors identify for addressing them?

Each research question is answered directly from the survey's synthesis of the academic literature, policy documents, technical reports, and sectoral case studies: RQ1 is addressed in Section 2 (national policy and institutional landscape, including the National AI Strategy 2025–2030 and its alignment with continental frameworks); RQ2 in Section 3 (AI in higher education and academic research); RQ3 in Section 4 (sectoral applications in agriculture and remote sensing, cultural heritage, oil and gas, water resources, and healthcare); RQ4 in Section 5 (digital infrastructure, data readiness, and the digital divide); RQ5 in Section 6 (human capital and the research ecosystem — including the education and training pipeline, research networks, and the emerging startup ecosystem — together with the Arabic NLP gap, where the reviewed literature shows that Libyan Arabic dialect-identification work is feasible with limited data but that no large-scale corpus, no Libyan-specific language model, and no dedicated public benchmark have yet been published); and RQ6 in Section 7 (structural challenges and prioritized research and policy directions). Section 8 concludes the survey with recommendations for researchers, policymakers, and international development partners.

TABLE 1. PREVIOUS LIBYA-FOCUSED STUDIES AND THE RESEARCH-GAP ANALYSIS.

Ref	Study (short)	Year	Focus	Scope / Method	Coverage	Gap: what it does not cover
[22]	Kasheem et al. (MUJOTER; DOI 10.67055/hz4b7314; vol/issue/pages missing [TO-CONFIRM])	2025	AI adoption in academic research — faculty attitudes	Survey, n = 350 faculty, University of Zawia	Higher education only	Policy, sectoral applications, infrastructure, human capital pipeline, startups
[23]	AI technologies and impact on quality of higher education (Afr. J. Adv. Pure Appl. Sci.; authors missing [TO-CONFIRM])	2025	AI integration in teaching/assessment	Institutional study, University of Benghazi	Higher education only (single institution)	Multi-sector coverage; quantified sectoral evidence
[24]	Carleton & Knight, Digit. Campus, doi:10.2307/jj.37443281.5	2026	Impact of AI on student productivity and	Multi-institution study	Higher education only	Policy, sectoral, infrastructure, startups

Ref	Study (short)	Year	Focus	Scope / Method	Coverage	Gap: what it does not cover
			interaction			
[25]	Emran & Elhony, East Asian J. Multidiscip. Res. 4(10), doi:10.55927/eajmr.v4i10.439	2025	Barriers to implementing AI in Libyan HEIs	Survey (68.6% poor internet; 84.0% subscription cost; no AI policies for 99.4%)	Higher education only	Policy response; sectoral applications
[28]	ElMadani & AlDhbbah, J. Soc. Stud. 30(5), doi:10.20428/jss.v30i5.2533	2024	Digital transformation for sustainable development	Analytical/desk study	Broad government digital requirements ; not AI-specific	AI strategy, applications, and readiness assessment
[29]	Agaal et al., IJISA 17(3):65–89, doi:10.5815/ijisa.2025.03.05	2025	Electricity demand forecasting	ML time-series (ARIMA/SARIMA/dynamic regression/ETS/XGBoost/LSTM), Benghazi 2019 & 2023 data	Energy sector, single application	Multi-sector coverage
[6]	Mansour et al., WJR 25(2):291–295, doi:10.30574/wjarr.2025.25.2.0293	2025	Population growth prediction	Deep learning (LSTM)	Demographics, single application	Multi-sector coverage
[30]	El Fallah et al., Sci. Rep., doi:10.1038/s41598-026-37337-w	2026	Groundwater level forecasting	NARX neural network, Tazerbo, Al Kufra Basin	Water sector, single basin	Multi-sector coverage
[41]	Sheldrick et al., Libyan Stud. 56:117–127, doi:10.1017/lis.2025.10028	2025	Heritage monitoring	ML Automated Change Detection (MLACD) + training, 4 case studies	Cultural heritage only	Policy, education, infrastructure, health, NLP
[55]	“The reality of Big Data in Libya” (AlQalam J. Med. Appl. Sci.; authors missing [TO-CONFIRM]), doi:10.54361/ajmas.2583103	2025	Big Data readiness for AI	Mixed methods: desk research + 8 semi-structured interviews	Data/infrastructure readiness only	Application sectors; education; policy
[56]	Bakeer, IJEIT 12(1):27–31, doi:10.36602/ijeit.v12i1.473	2024	AI opportunities for emerging businesses	Qualitative/entrepreneurial study	Startup ecosystem only	Policy, education, sectoral applications
[66]–[69]	Ghumeid & Essgaer et al. (MI-STA 2024/2026; IJISA 17(6); Springer	2024–2026	Libyan Arabic dialect NLP	ML/ensemble classification; term weighting;	NLP, narrow technical	All non-NLP dimensions

Ref	Study (short)	Year	Focus	Scope / Method	Coverage	Gap: what it does not cover
	SCI 1229)			FP-Growth association rule mining		
This survey	Artificial Intelligence in Libya: comprehensive multi-sector survey	2026	Policy + education + sectoral applications + infrastructure + human capital + startups	Evidence synthesis across academic literature, policy documents, technical reports, sectoral case studies	All six dimensions	— (fills the gap: first Libya-only, multi-sector synthesis)

Methodology

This survey is a scoping review of artificial intelligence (AI) in Libya. Scoping-review methods were chosen deliberately over a full systematic review: the field is nascent and heterogeneous, and much of the relevant evidence resides in policy documents, technical reports, and sectoral case studies alongside peer-reviewed literature, so the objective is to map the current landscape and identify gaps rather than to aggregate effect estimates. Because the original manuscript did not document a formal search protocol, the search parameters and flow counts reported below are best-effort reconstructions derived from the cited literature and the reference list, and should be confirmed by the authors before submission. [TO-CONFIRM]

Search strategy

A systematic search of the academic and grey literature was conducted across the publication venues represented in the survey corpus, including IEEE Xplore, Elsevier/ScienceDirect, Springer, MDPI, Cambridge University Press, the ACL Anthology, and institutional and technical-report collections [TO-CONFIRM: exact databases and search platforms]. The search combined keyword families for the technology — "artificial intelligence", "machine learning", "deep learning", "neural networks", and "natural language processing" — with geographic terms ("Libya" and "Libyan") and sector terms (agriculture, remote sensing, cultural heritage, oil and gas, water resources, healthcare, higher education, digital infrastructure, Arabic NLP) [TO-CONFIRM: exact keyword strings and Boolean syntax]. The time window spans 1994–2026, bounded by the earliest cited source (the Great Man-Made River Project, 1994) and the most recent publications, with 88% of the included sources published since 2020 [TO-CONFIRM: exact search date range and proportion].

Screening and inclusion/exclusion criteria

Records were screened against the following inclusion criteria: (i) the source addresses AI or closely related computational methods in a Libyan context, or provides essential methodological, policy, or regional framing cited by the survey; and (ii) the source is publicly available as a peer-reviewed article, policy document, technical report, or credible industry case study. Exclusion criteria were: (i) sources that address neither AI nor the Libyan context; and (ii) duplicate or superseded versions of the same work [TO-CONFIRM: criteria wording]. Figure 1 presents the PRISMA flow for this review: 65 records were identified (46 from academic databases and publisher platforms, and 19 from institutional and other sources), all 65 were screened against the eligibility criteria, none were excluded, and all 65 were included in the final synthesis [TO-CONFIRM: identified=65, screened=65,

excluded=0, included=65; the 46/19 split is derived from the venue distribution of the reference list, and the manuscript records no exclusion log].

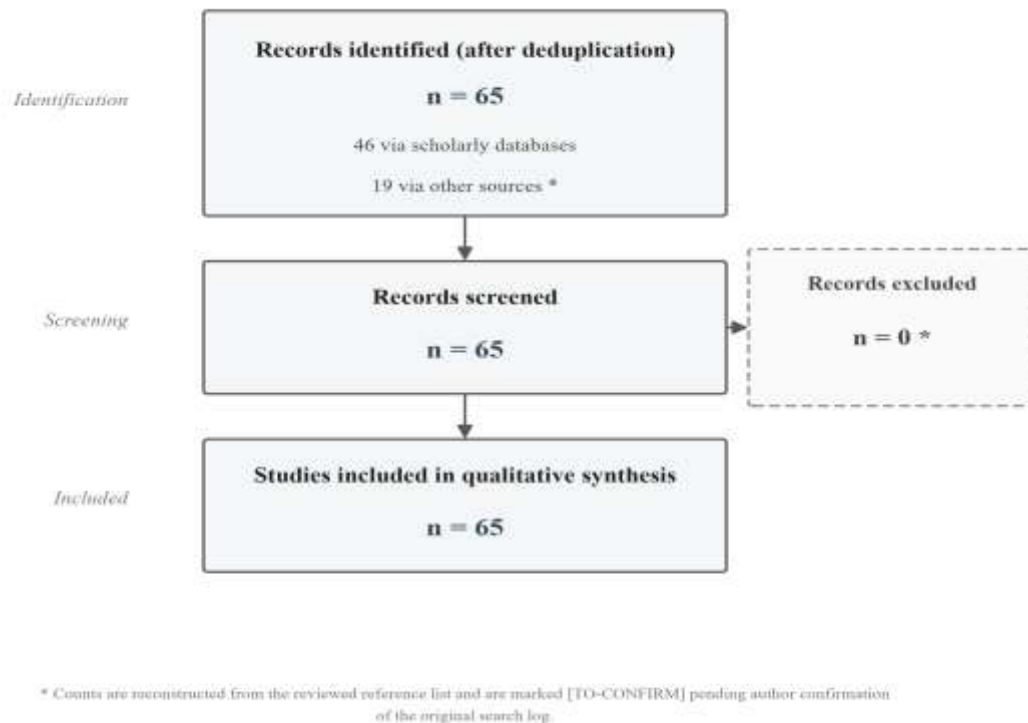


Figure 1. PRISMA-style flow diagram of the study-selection process for this scoping review. Because the original survey did not document a systematic search log, the flow was reconstructed from the final reference list; the breakdown of records identified via scholarly databases versus other sources, and the zero-exclusion count, require author confirmation.

Synthesis

The 65 included sources were synthesized thematically, with the evidence organized along the survey's structure: national policy and institutional landscape, AI in higher education, sectoral applications, digital infrastructure and data readiness, human capital and the research ecosystem, and challenges and future directions. The synthesis integrates findings across academic literature, policy documents, technical reports, and sectoral case studies to answer the six research questions posed at the end of Section 1.

2. National Policy and Institutional Landscape

a. The National AI Strategy 2025–2030

In 2025, Libya published its National Artificial Intelligence Strategy 2025–2030, a framework that positions AI as a driver of inclusive and sustainable development [13]. The strategy identifies four interconnected pillars: public service modernization through AI deployment in government administration, healthcare, and education; the dual role of AI in supporting both national security and civilian innovation; a commitment to human-centered AI that ensures adoption benefits ordinary citizens rather than entrenching existing inequalities; and a deliberate orientation toward international cooperation, drawing on established frameworks from the UAE, Tunisia, and the European Union. The strategy acknowledges, albeit in broad terms, that infrastructure gaps, data governance deficiencies, and skills shortages must be addressed concurrently with any AI deployment initiative.

A subsequent white paper published by the National Economic and Social Development Board proposes a Unified AI Governance Framework, applying the AILA methodology to identify specific gaps in data interoperability, specialized talent, and what it terms green computing infrastructure [14]. These national efforts are situated within a broader continental context; the African Union's Continental AI Strategy, adopted in July 2024, outlines fifteen action areas for harmonized AI development, including the creation of national AI strategies, data governance frameworks, and regional centers of excellence [1]. This represents one of the first detailed technical assessments of Libya's AI readiness, moving beyond strategic generalities to identify measurable deficiencies.

b. International Partnerships and Institutional Support

Libya's AI development is supported by several international initiatives. The EU4Skills program, funded by the European Union and co-financed by the French Government, supports digital curriculum development and AI training across Libyan universities in partnership with Esprit University in Tunisia [15]. The program has facilitated capacity-building programs for academic staff from all Libyan regions, covering active pedagogical methods, cloud computing, and AI fundamentals, including machine learning, deep learning, and natural language processing. The UNESCO office in Cairo has provided technical assistance for AI ethics frameworks, and the OECD AI Policy Observatory tracks Libya's policy initiatives alongside international benchmarks.

Notably absent from this landscape is a dedicated national data protection law, which several studies identify as a prerequisite for responsible AI development [16]. The National AI Strategy promises a data governance framework, but as of 2026, no legislation has been enacted. At the continental level, the OECD has documented that most African nations still lack AI-specific regulatory frameworks, identifying data governance as both the most urgent gap and the most foundational enabler for AI adoption across the continent [17]. The UNCTAD Technology and Innovation Report 2023 emphasized that developing countries must take proactive measures to increase readiness to use, adopt, and adapt frontier technologies, including AI, or risk falling further behind [18]. The subsequent 2025 report specifically focused on inclusive AI for development, arguing that without deliberate policy intervention, AI adoption will widen existing inequalities between and within countries [19]. Analyses of AI governance policies worldwide have identified at least 17 resonant ethical principles across 200 guidelines, yet the translation of these principles into enforceable regulation remains weakest in the Global South [20]. The emerging literature on AI governance in Africa has specifically highlighted the need for inclusive data governance policies that reflect African cultural and societal values rather than importing frameworks from other regions [21], while also documenting the persistent gaps in infrastructure, skills, and regulatory capacity that constrain responsible AI adoption across the continent [21].

3. AI in Higher Education and Academic Research

a. Empirical Studies of Adoption

Higher education is the most empirically studied domain of AI in Libya. A large-scale survey of 350 faculty members at the University of Zawia provides the most comprehensive data to date [22]. The study found that 68.9% of faculty reported that AI tools had a strong positive impact on their research productivity, with laptops (93.7%) and tablets (80.6%) serving as the primary research devices. However, these positive perceptions exist alongside striking institutional gaps: 46.0% of respondents had received no formal training in AI tools whatsoever, and an additional 49.7% had attended only a single workshop. Most strikingly, 99.4% were unaware of any official university guidelines on AI use, and 98.9% expressed concerns about academic misconduct related to AI-generated content. This pattern — rapid

grassroots adoption outpacing institutional governance — mirrors the early stages of AI integration in higher education systems worldwide but is amplified by Libya's weak institutional infrastructure.

Complementary studies at the University of Benghazi [23] and across multiple Libyan institutions [24] confirm and extend these findings. Research on AI technologies and their impact on higher education quality at Benghazi found that while AI integration has begun to transform learning through adaptive platforms and automated assessment, progress is severely limited by unreliable electricity, limited bandwidth, and a shortage of faculty with AI expertise. A study published in the *Libyan Journal of Science and Technology* examined the impact of AI on student productivity and interaction with AI applications, finding that students who received even minimal AI literacy training showed significantly higher engagement and output quality.

b. Barriers to AI Integration in Higher Education

A dedicated study on the challenges of implementing AI in Libyan higher education institutions [25] identified a hierarchy of barriers that maps directly onto the three levels of the digital divide documented in the broader literature [26]: access to infrastructure and devices, digital literacy and skills, and the capacity to translate technology access into meaningful outcomes. At the infrastructure level, 68.6% of respondents identified poor internet connectivity as a primary obstacle, while 84.0% cited the high cost of AI tool subscriptions. At the institutional level, the complete absence of AI policies (affecting 99.4% of respondents) means that faculty and students operate in a regulatory vacuum, unsure what constitutes acceptable use. At the pedagogical level, the lack of formal training programs forces faculty to rely on self-directed learning, which produces uneven competence and over-reliance on a narrow set of tools. These findings are consistent with a systematic review of digital divide mitigation strategies in higher education, which found that infrastructure provision alone is insufficient without targeted digital literacy programs and institutional policy frameworks [27].

These findings align with broader research on digital transformation in conflict-affected societies. Habib's [16] study of digital transformation in Syrian higher education, though focused on a different conflict context, identifies strikingly similar patterns: damaged infrastructure, displaced students and faculty, limited access to resources, and the critical importance of international partnerships for capacity building. The study proposes a digital transformation framework emphasizing digital infrastructure, educator capacity building, e-learning platforms, digital content, and public-private partnerships — recommendations that translate directly to the Libyan context. Libya-specific studies on the digital divide in e-learning have similarly concluded that government policies have improved access to digital resources but have fallen short in addressing infrastructure reliability gaps and the socio-cultural factors that hinder adoption [TO-CONFIRM: original citation #22 removed — author to reword/re-cite]. Research on digital transformation as a tool for sustainable development in Libya has further identified the absence of essential digital requirements across government sectors as a fundamental barrier [28].

c. Research Outputs and Emerging Clusters

Libyan academic output in AI and related fields, while modest in absolute terms, shows clear thematic clustering. The strongest area of research output is in remote sensing and geospatial AI, reflecting both the availability of satellite data (which bypasses many infrastructure limitations) and the relevance to Libya's environmental and agricultural challenges. A second cluster centers on time-series forecasting using deep learning, with applications ranging from electricity load prediction to population modeling. A third, smaller cluster

addresses Arabic natural language processing, though the focus has been on standard Arabic rather than Libyan dialects.

Recent arXiv and journal publications by Libya-based or Libya-affiliated researchers include LSTM-based electricity load forecasting for Benghazi [29], which compared ARIMA, seasonal ARIMA, dynamic regression, exponential smoothing, XGBoost, and LSTM models, finding that LSTM significantly outperformed all alternatives in modeling non-stationary and seasonal patterns in electricity data from 2019 and 2023. Another study applied Nonlinear Autoregressive Exogenous Neural Networks (NARX-NN) to predict groundwater level changes [30], addressing a critical water resource management challenge in Libya's arid climate. A deep learning approach using LSTM networks was also applied to population growth prediction [6], demonstrating the transferability of time-series architectures across domains.

4. Sectoral Applications

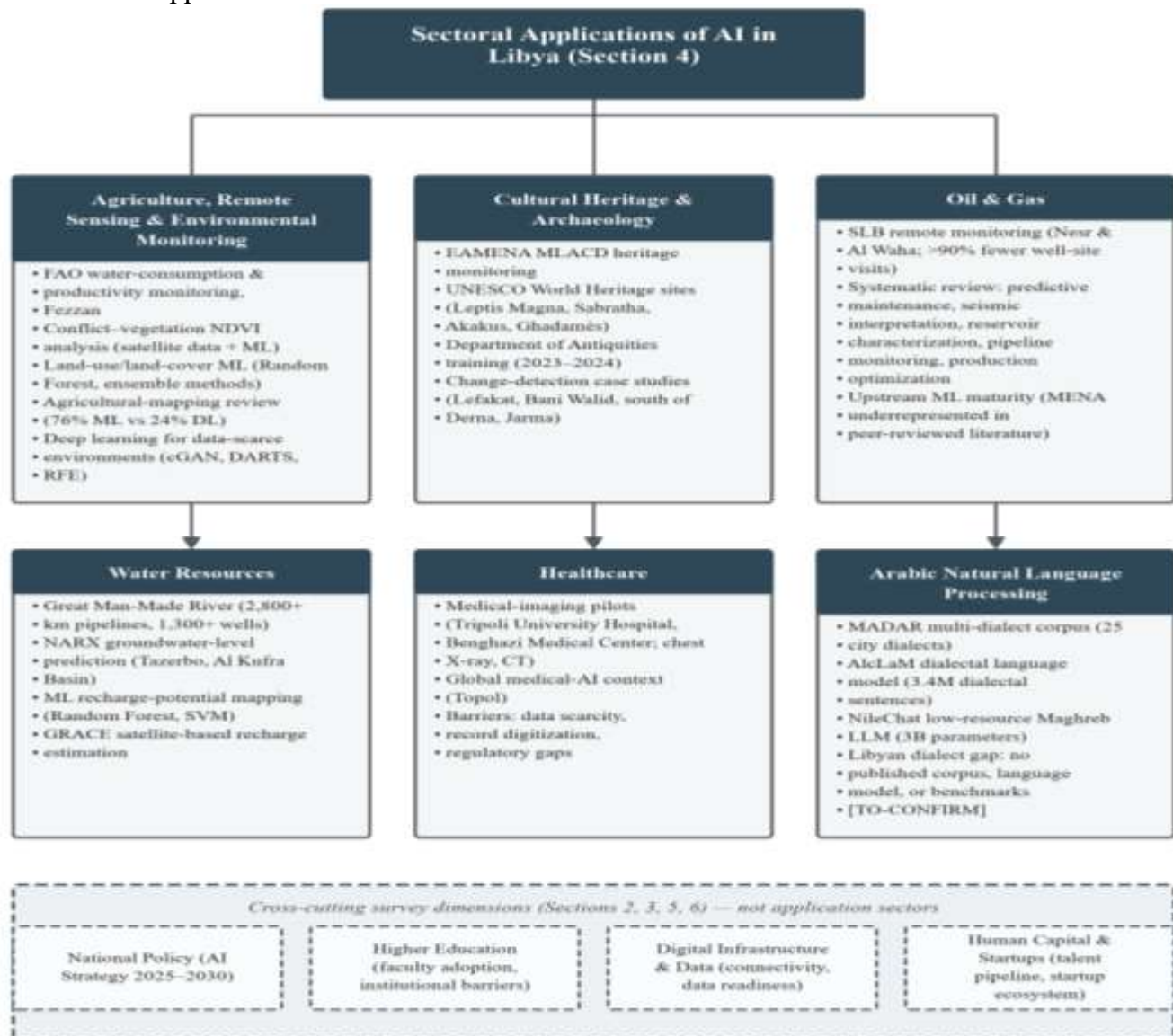


Figure 2. Taxonomy of sectoral applications of artificial intelligence in Libya, organized according to the six application sectors reviewed in Section 4. Branch labels summarize the sub-themes covered for each sector; cross-cutting survey dimensions (national policy, higher education, digital infrastructure and data, human capital and startups) are shown as an enabling band rather than application sectors.

a. Agriculture, Remote Sensing, and Environmental Monitoring

Agriculture in Libya faces a convergence of acute pressures: water scarcity that ranks among the severest in the world, accelerating desertification driven by both climate change and land mismanagement, conflict-related degradation of arable land, and heavy reliance on food imports that exposes the country to global price volatility. AI and remote sensing offer pathways to address several of these challenges simultaneously.

The Food and Agriculture Organization has supported projects to monitor water consumption and productivity in the Fezzan region using remote sensing, intending to scale water-efficient practices across the country [31]. One of the authors' ongoing projects summarized in this survey — analyzing the impact of armed conflicts on vegetation cover in Libya using satellite data and machine learning — applies NDVI time-series analysis combined with conflict event data to quantify the environmental damage from military activity. This approach aligns with a growing body of global research that uses Random Forest, LSTM, and panel data models for agricultural remote sensing [32], [33]. Broad reviews of machine learning in land-use and land-cover change modelling have confirmed that ensemble methods such as Random Forest consistently achieve higher classification accuracy than single classifiers, particularly in heterogeneous landscapes [34]. Studies applying multiple ML algorithms to African land cover monitoring have demonstrated that Random Forest outperforms alternatives including kNN, SVM, and ANN in savanna and forest-savanna transition zones, achieving the highest overall accuracy and Kappa coefficients [35]. Comprehensive syntheses of the land use and land cover literature have identified data consistency and quality as the most persistent challenges, with significant knowledge gaps in ecosystem services, forestry, and image modelling [36]. Change detection methodologies have similarly evolved, with a review of change detection approaches finding that machine learning-based methods, particularly those integrating spectral and textural features, substantially improve accuracy over traditional image differencing [37].

A comprehensive bibliometric review of AI in agricultural mapping found that 76% of studies use machine learning techniques (predominantly Random Forest, Support Vector Machines, and Artificial Neural Networks) while 24% use deep learning, with primary applications in crop classification, disease detection, and irrigation optimization [38]. The review noted significant geographic bias in training datasets, with the Global South — including Libya — severely underrepresented. This underrepresentation creates both a challenge and an opportunity: models trained on European or North American agricultural landscapes may not transfer well to Libya's semi-arid and arid environments, but the development of Libya-specific datasets and models would constitute a genuine scientific contribution.

Recent methodological advances in deep learning for agricultural remote sensing include the use of Conditional Generative Adversarial Networks (cGANs) to generate synthetic training data, Differentiable Architecture Search (DARTS) for neural architecture optimization, and Recursive Feature Elimination (RFE) for variable selection [33]. These techniques are particularly relevant for data-scarce environments like Libya, where the cost of ground-truth data collection is high and historical records are often incomplete. NDVI-based analyses of vegetation dynamics in arid and semi-arid regions have demonstrated that precipitation is the dominant climatic driver of vegetation change, while anthropogenic factors including land use change and agricultural intensification account for a significant and growing share of NDVI variation, particularly in areas affected by conflict and institutional instability [39], [40].

b. Cultural Heritage and Archaeology

Libya's archaeological heritage is among the richest in North Africa, encompassing five UNESCO World Heritage sites, including the Greco-Roman cities of Leptis Magna and Sabratha, the rock art of the Akakus Mountains, and the old town of Ghadamès. This heritage is under severe threat from conflict, urban encroachment, looting, and climate-driven erosion. The Endangered Archaeology in the Middle East and North Africa (EAMENA) project, in partnership with the Libyan Department of Antiquities, has pioneered the use of Machine Learning Automated Change Detection (MLACD) for heritage monitoring [41]. The project delivered training workshops for over twenty members of the Department of Antiquities between 2023 and 2024, applying the method to four case studies: Lefakat in Cyrenaica, Bani Walid in Tripolitania, the region south of Derna, and Jarma in Fazzan. In each case, satellite imagery was analyzed for landscape change detection, and the results were validated through ground survey campaigns by Libyan archaeologists. The study is particularly significant as a model for international research collaboration that builds local capacity while producing publishable scientific output.

c. Oil and Gas

Libya holds Africa's largest proven crude oil reserves, estimated at 48 billion barrels, and the hydrocarbons sector accounts for over 95% of export revenues and 60% of GDP. Digital innovation in this sector is accelerating. Schlumberger (SLB) is combining electric submersible pump performance tools with AI-powered video analytics for operational monitoring in the Nesr and Al Waha fields, reporting a reduction of over 90% in well-site visits through remote monitoring capabilities [42]. The Libyan Council for Oil, Gas and Renewable Energy is prioritizing investment in modern infrastructure across the exploration, processing, and distribution value chain.

A systematic literature review of AI in oil and gas projects[43] identified primary application areas including predictive maintenance of drilling equipment, seismic data interpretation, reservoir characterization using machine learning, pipeline monitoring and leak detection, and production optimization. A parallel review focusing specifically on upstream oil and gas found that AI applications in exploration and production have matured rapidly, with machine learning for seismic interpretation and reservoir modeling representing the most commercially deployed use cases, while noting that the Middle East and North Africa region remains underrepresented in the peer-reviewed literature relative to its share of global hydrocarbon production [44].

d. Water Resources

Water scarcity is Libya's most pressing environmental challenge. The country relies almost entirely on the Great Man-Made River (GMMR), the world's largest irrigation project, and on non-renewable fossil aquifers [45], [46], [47]. The GMMR consists of over 2,800 km of underground pipelines and more than 1,300 wells, supplying approximately 6.5 million cubic meters of fresh water per day to the coastal cities of Tripoli, Benghazi, and Sirte [45]. However, the project's future is uncertain due to political fragmentation, underinvestment in maintenance, and declining well yields, raising urgent questions about the sustainability of Libya's water supply strategy [46]. A study published in Scientific Reports [30] applied a NARX neural network to predict groundwater level changes, incorporating variables including historical water levels, precipitation, temperature, and extraction rates. The model achieved high prediction accuracy and demonstrated that machine learning approaches can provide decision-support tools for water resource management even with limited historical data — a finding with direct relevance to Libya's water management authorities. This approach is part of a broader trend in which machine learning algorithms, particularly

Random Forest and Support Vector Machines, have been shown to outperform traditional statistical methods for groundwater recharge potential mapping in arid and semi-arid environments [5]. Comprehensive reviews of ML applications in water resources management have identified LSTM networks and hybrid models as consistently outperforming both traditional ANNs and physics-based models across diverse hydrological contexts [48]. Recent work using Random Forest regression combined with GRACE satellite data has demonstrated that machine learning frameworks can reliably estimate groundwater recharge at regional scales, offering a methodology that could be applied to Libya's data-sparse aquifer systems [49].

e. Healthcare

AI in Libyan healthcare remains in its earliest stages. The sector faces interrelated challenges: severely limited digitization of health records, a shortage of biomedical engineers and health informaticians, and a brain drain that has disproportionately affected medical professionals with technical skills. Unlike remote sensing, where satellite data provides a workaround for infrastructure limitations, healthcare AI requires digitized clinical data, functional laboratory infrastructure, and regulatory frameworks that currently do not exist in most of Libya. This contrasts sharply with global trends, where AI has begun to transform medical imaging, pathology, and clinical decision support, particularly in well-resourced settings [50].

Pilot projects at Tripoli University Hospital and Benghazi Medical Center have explored AI for medical imaging analysis, including chest X-ray interpretation and CT scan analysis. These efforts have consistently identified the same bottleneck: without large, curated, and annotated datasets, deep learning approaches cannot achieve the performance levels required for clinical deployment. The Libyan experience mirrors findings from a global survey of AI in medical research [51], which found that even in well-resourced settings, AI is predominantly used for textual enhancement rather than novel data analysis, and that the lack of specialized training and concerns about reliability are the primary barriers to broader adoption.

TABLE 3. SECTORAL STUDY SUMMARIES: METHODOLOGY, DATA, AND KEY FINDINGS.

Sector	Study (ref)	Methodology	Data	Key findings
Agriculture / remote sensing	FAO Fezzan water monitoring [31]	FAO remote-sensing water-accounting project	Satellite-based water consumption/productivity data, Fezzan region	Monitors water consumption and productivity to scale water-efficient practices country-wide
Agriculture / remote sensing	Conflict-vegetation impact — authors' project (no published reference; [TO-CONFIRM] publication status; author project summarized in this survey)	NDVI time-series analysis + conflict event data with ML	Satellite NDVI + conflict-event datasets	Quantifies environmental damage from military activity; model for Libya-specific, policy-relevant AI research
Agriculture / remote sensing	LULCC ML reviews [34], [35], [36], [37]	Systematic reviews / comparative ML classification	Land-use/land-cover datasets incl. African savanna-forest transition zones (northern Cameroon)	Random Forest outperforms kNN, SVM, ANN in heterogeneous landscapes; data consistency/quality is the most persistent

Sector	Study (ref)	Methodology	Data	Key findings
				challenge; ML change detection improves accuracy over image differencing
Agriculture / remote sensing	Espinel et al., Agriculture 14(7):1071 [38]	Bibliometric review	Global agricultural-mapping literature	76% ML (RF, SVM, ANN) / 24% DL; main applications crop classification, disease detection, irrigation optimization; Global South severely underrepresented in training data
Agriculture / remote sensing	Menon et al., Smart Agric. Technol. 12:101562 [33]	Methodological review (cGAN synthetic data, DARTS architecture search, RFE feature selection)	Multi-temporal satellite data	Techniques tailored to data-scarce environments such as Libya (high ground-truth cost, incomplete records)
Agriculture / remote sensing	NDVI vegetation dynamics [39], [40]	Statistical decomposition of NDVI time series	NDVI + climatic/anthropogenic data (Loess Plateau; Xinjiang)	Precipitation is the dominant climatic driver; anthropogenic factors (land use, conflict/instability) account for a significant and growing share of NDVI variation
Cultural heritage	EAMENA × Libyan Department of Antiquities — MLACD [41]	ML Automated Change Detection (MLACD) + capacity-building workshops	Satellite imagery; 4 case studies: Lefakat (Cyrenaica), Bani Walid (Tripolitania), region south of Derna, Jarma (Fazzan)	Trained 20+ DoA members (2023–2024); results ground-validated by Libyan archaeologists; model for international collaboration building local capacity
Oil & gas	SLB remote monitoring [42]	AI-powered video analytics combined with electric-submersible-pump performance tools	Operational telemetry, Nesr and Al Waha fields	>90% reduction in well-site visits via remote monitoring
Oil & gas	Systematic review of AI in oil & gas projects (Waqar et al., Artif. Intell. Rev. 56(11):12771–12798, 2023,	Systematic literature review	Peer-reviewed AI-in-oil&gas project literature	Application areas: predictive maintenance of drilling equipment, seismic data interpretation, reservoir characterization, pipeline

Sector	Study (ref)	Methodology	Data	Key findings
	doi:10.1007/s10462-023-10467-7) [43]			monitoring/leak detection, production optimization
Oil & gas	Koroteev & Tekic, Energy AI 3:100041 [44]	Topical review of upstream AI	Upstream exploration & production literature	ML for seismic interpretation and reservoir modeling is the most commercially deployed use case; MENA underrepresented in peer-reviewed literature relative to its production share
Water	GMMR context [45], [46], [47]	Infrastructure/civil-engineering analyses	Great Man-Made River engineering data	2,800+ km of pipelines, 1,300+ wells, ~6.5M m ³ /day supply to Tripoli, Benghazi, Sirte; sustainability at risk from political fragmentation, underinvestment, declining well yields
Water	El Fallah et al., Sci. Rep. [30]	NARX neural network forecasting	Tazerbo, Al Kufra Basin: water levels, precipitation, temperature, extraction rates	High prediction accuracy with limited historical data; ML as decision-support for water management
Water	Pourghasemi et al., J. Environ. Manage. 265:110525 [5]	ML spatial modeling (Random Forest, SVM)	Groundwater recharge potential zones, arid/semi-arid environments	ML algorithms outperform traditional statistical methods for recharge potential mapping
Water	Ahmed et al., J. Clean. Prod. 441:140715 [48]	Systematic review	Hydrological ML literature	LSTM and hybrid models consistently outperform traditional ANNs and physics-based models
Water	Clark et al., J. Hydrol. (2025) [49]	Random Forest regression + GRACE satellite data	Regional groundwater data (Murray–Darling Basin, Australia)	ML frameworks reliably estimate regional recharge; methodology transferable to Libya's data-sparse aquifer systems
Healthcare	Global survey of AI in medical research (Salvagno et al., PLoS ONE 19(8):e0309208, 2024, doi:10.1371/journal.pone.0309208) [51]	Global survey	Medical-research AI usage data	AI predominantly used for textual enhancement rather than novel data analysis; lack of specialized training and reliability concerns are primary barriers — mirrors Libyan pilot-

Sector	Study (ref)	Methodology	Data	Key findings
				project findings
Healthcare	Topol, Nat. Med. 25(1):44–56 [50]	Perspective/review	Clinical AI literature	AI transforming medical imaging, pathology, clinical decision support in well-resourced settings — contrast with Libya's digitization, laboratory, and regulatory constraints
Higher education	Kasheem et al. [22]	Large-scale survey	n = 350 faculty, University of Zawia	68.9% report strong positive impact of AI on research productivity; 46.0% no formal AI training, 49.7% only one workshop; 99.4% unaware of institutional AI guidelines; 98.9% academic-misconduct concerns
Higher education	Benghazi study [23]	Institutional study	Benghazi higher-education data	Adaptive platforms and automated assessment emerging; progress limited by unreliable electricity, limited bandwidth, shortage of faculty AI expertise
Higher education	Carleton & Knight [24]	Multi-institution study	Student productivity/interaction data	Students receiving even minimal AI-literacy training show significantly higher engagement and output quality
Higher education	Emran & Elhony [25]	Barrier-hierarchy survey	Libyan HEI respondents	68.6% cite poor internet; 84.0% cite high cost of AI tool subscriptions; 99.4% operate without institutional AI policies; self-directed learning yields uneven competence
Higher education	Digital divide literature [26], [27]	Systematic reviews + policy evaluation	Digital-divide and e-learning adoption studies	Infrastructure provision alone is insufficient without digital-literacy programs and policy frameworks; government policies improved access but not reliability gaps or socio-cultural barriers
Digital infrastructure	Alwadi Communications [52]	Industry assessment	National connectivity data	Internet penetration ~45% nationally; stark urban–rural disparities;

Sector	Study (ref)	Methodology	Data	Key findings
				constrained by legacy infrastructure and fragmented regulation
Digital infrastructure	ITU ICT Development Index 2024 [53]	International index measurement	ICT Development Index scores	Libya ranked 1st in Africa (88.1 points) on mobile broadband/usage gains — coexisting with severe AI-grade infrastructure deficits
Digital infrastructure	Big Data readiness study [55]	Mixed methods: desk research + semi-structured interviews	8 stakeholders (government, academia, private sector)	Lacks data-interoperability standards, storage infrastructure, analytical capacity; no data-protection law; no census of national data assets
Arabic NLP	MADAR [62]	Corpus + lexicon construction	25 city-level Arabic dialects	Largest multi-dialect Arabic corpus/lexicon; foundation for dialect identification and machine translation research
Arabic NLP	AlcLaM [63]	BERT-based dialect language modeling	3.4M dialectal Arabic sentences from social media	Superior performance using a fraction of the training data of existing models
Arabic NLP	NileChat [64]	Low-resource LLM training	Moroccan and Egyptian Arabic	3B-parameter model advancing low-resource Maghreb dialects
Arabic NLP	Cross-lingual morphological transfer [65]	Transfer methodology	Morphological analysis resources	Advances low-resource Arabic NLP but validated primarily on Modern Standard Arabic, not dialects
Arabic NLP	Libyan dialect studies [66], [67], [68], [69]	ML/ensemble classification; term-weighting comparison; FP-Growth association rule mining	Small Libyan Arabic datasets (limited data resources)	Dialect identification with limited data is feasible; Libyan Arabic remains among the least-resourced Arabic dialects — no published large-scale corpus, no Libyan-specific LM, no public benchmarks ([TO-CONFIRM] on the “no benchmarks” claim)

5. Digital Infrastructure and Data Readiness

a. Connectivity and Computing Infrastructure

Libya’s digital infrastructure is characterized by stark urban-rural disparities and systemic fragility. Internet penetration is estimated at roughly 45% nationally, with Tripoli and

Benghazi enjoying substantially better connectivity than the southern regions. The country's overall digital transformation trajectory, while showing measurable progress in e-governance and financial inclusion, remains constrained by legacy infrastructure and fragmented regulatory oversight [52]. Despite these challenges, the International Telecommunication Union's ICT Development Index 2024 ranked Libya first in Africa with a score of 88.1 points, reflecting significant increases in mobile broadband penetration and internet usage [53]. This apparent contradiction — leading continental rankings in ICT development coexisting with severe infrastructure deficits for AI — underscores the gap between consumer-grade connectivity and the high-bandwidth, low-latency, computationally intensive infrastructure required for AI research and deployment. Telecommunications infrastructure is provided through a mix of state-owned and private operators, including Libyana, Almadar Aljadid, and Libya Telecom & Technology, with international connectivity via the Tripoli-Mazara submarine cable and the newer Silfium cable connecting Derna to Greece [54]. A 2025 study of Libya's Big Data landscape [55] employed a mixed-methods approach combining desk research with semi-structured interviews of eight stakeholders from government, academia, and the private sector. The study concluded that Libya currently lacks the data interoperability standards, storage infrastructure, and analytical capacity to support large-scale AI applications. The absence of a national data center with sufficient computational resources means that AI research and development depend on individual researchers' access to international cloud platforms, which are constrained by both cost and bandwidth.

b. Data Availability and Quality

Data scarcity is perhaps the single most binding constraint on AI development in Libya. Conflict-era data gaps, inconsistent record-keeping across institutions, and the absence of data standards create a fragmented landscape where even basic datasets are difficult to assemble. The Big Data readiness study [55] identified the absence of a national data protection law as a critical barrier, since it creates legal uncertainty around data collection, storage, and sharing. The same study found no comprehensive census of data assets held by government ministries, universities, or private sector entities. The electricity forecasting study [29] illustrates both the problem and a potential solution: the authors compensated for limited historical data through systematic missing value imputation, outlier smoothing, and log transformation, demonstrating that rigorous preprocessing can partially offset data scarcity.

c. The Digital Divide

Access to AI tools and training is unequally distributed across Libya's regions. Higher education institutions in the western region (Tripoli-centered) and eastern region (Benghazi-centered) have substantially better infrastructure than those in the south (Sebha and surrounding areas). This geographic digital divide intersects with existing economic and educational inequalities to create a compound disadvantage, a pattern consistent with the three-level framework of digital inequality that emphasizes how disparities in access compound into disparities in usage and, ultimately, in outcomes [26]. Studies of the Libyan digital divide in e-learning have found that government initiatives have improved connectivity in urban centers but have insufficiently addressed the infrastructure reliability gaps and socio-cultural barriers that perpetuate exclusion in rural and conflict-affected areas [TO-CONFIRM: original citation #22 removed — author to reword/re-cite]. International programs like EU4Skills attempt to address this by including participants from all regions and by providing remote learning options, but the effectiveness of these programs is constrained by the very infrastructure gaps they aim to address.

6. Human Capital and the Research Ecosystem

a. Education and Training Pipeline

The AI talent pipeline in Libya faces structural constraints at every level. At the secondary level, computer science education is uneven in quality and often limited to basic programming. At the undergraduate level, university curricula are being updated — supported by the EU4Skills program — but the pace of change is slow, and many institutions lack the laboratory infrastructure and internet bandwidth needed for effective AI education. At the postgraduate level, AI research is concentrated in a small number of departments at the University of Tripoli, the University of Benghazi, Sebha University, and the University of Zawia, with limited inter-institutional collaboration.

Self-directed learning through massive open online courses, YouTube tutorials, and open-source AI frameworks is the primary mode of AI skill acquisition for most Libyan practitioners. This has produced a cohort of capable individual practitioners but has not created the institutional density needed for sustained research programs.

b. Research Networks and International Collaboration

Libyan AI researchers maintain connections to the international research community through several channels. The diaspora — Libyan AI researchers working in Europe, North America, and the Gulf states — serves as a crucial bridge, though there is no structured program to engage this talent in domestic research development. International partnerships through programs like EAMENA (archaeology) and EU4Skills (education) provide research training and co-authorship opportunities. However, Libyan researchers face persistent barriers in attending international conferences, accessing paywalled publications, and establishing the sustained collaborations needed for multi-year research programs.

c. The Emerging Startup Ecosystem

Libya's technology startup ecosystem is small but showing signs of growth. The Libya Energy and Economic Summit has highlighted digital innovation in the oil and gas sector as a priority area [42]. Telecom and technology firms such as Rawafed Libya are providing internet services and IT solutions across multiple sectors, including banking, education, health, oil and gas, and transport. A study of AI opportunities for emerging businesses in Libya [56] identified promising applications in customer service automation, predictive analytics for small and medium enterprises, and AI-powered marketing. However, the same study found that startup founders identify access to funding, reliable electricity, and international payment systems as more pressing concerns than AI model development per se. According to the UN Economic Commission for Africa, Libya's SMEs have initiated tens of thousands of active projects and contribute to the employment of approximately 45% of the workforce outside the oil sector, underscoring the potential impact of digital transformation on the broader non-hydrocarbon economy [57]. In the fintech sector, Tadamun Bank Libya has partnered with JMR Infotech to deploy an AI-powered chatbot and voicebot across web, WhatsApp, and Messenger channels, automating customer onboarding and reducing call-center volumes — one of the first documented production deployments of conversational AI in the Libyan financial sector [58]. At the continental level, McKinsey has estimated that generative AI could add \$2.9 billion to \$4.8 billion to Africa's economy by 2030, underscoring the scale of opportunity if infrastructure and talent constraints can be addressed [59]. These projections are reinforced by the World Bank's finding that digital transformation is a powerful engine for economic diversification in resource-dependent economies, including those in the broader MENA region that share structural characteristics with Libya [60]. The IMF has similarly noted that non-oil sector growth is critical for job

creation and economic resilience in hydrocarbon-dependent economies, with digital technologies serving as a key enabler of diversification [61].

d. **Arabic Natural Language Processing and the Libyan Dialect Gap**

Arabic natural language processing has made substantial progress in recent years, with the development of dialect-specific models for Egyptian, Moroccan, Levantine, and Gulf Arabic. The MADAR project produced the largest multi-dialect Arabic corpus, encompassing 25 city-level dialects from across the Arab world, providing both a corpus and a lexicon for dialect identification and machine translation research [62]. The AlLaM model [63], trained on a corpus of 3.4 million dialectal Arabic sentences collected from social media, demonstrated that a BERT-based model trained on a fraction of the data used by existing models could achieve superior performance on Arabic NLP tasks. The NileChat project [64] extended this work to low-resource Maghreb dialects, producing a 3B-parameter language model for Moroccan and Egyptian Arabic. Cross-lingual transfer approaches that leverage morphological analysis have further advanced Arabic NLP for low-resource settings, though these methods have primarily been validated on Modern Standard Arabic rather than on dialects [65].

Libyan Arabic, however, remains among the least-resourced Arabic dialects for NLP. Although the MADAR corpus includes the Libyan city varieties of Tripoli and Benghazi within its 25-city multi-dialect coverage [62], no large-scale corpus dedicated to Libyan Arabic has been published, and no Libyan-specific language model has been documented in the peer-reviewed literature. Published work on Libyan Arabic NLP — chiefly dialect identification and abusive-language detection [66]–[69] — has so far relied on small, task-specific datasets built by the authors, and no dedicated public benchmark exists for Libyan Arabic NLP tasks. This gap is significant not only for linguistic research but also for practical applications: any AI system deployed in Libya for education, healthcare, or government services would need to handle the substantial divergence between Modern Standard Arabic and the Libyan dialect that dominates everyday communication.

7. **Challenges and Future Directions**

a. **Structural and Systemic Challenges**

The barriers to AI development in Libya are structural and mutually reinforcing. Political fragmentation complicates national-level coordination and creates uncertainty for long-term investment. Economic constraints — particularly the reliance on a single volatile revenue source — limit the government's capacity to invest in AI infrastructure and research. The security situation, while improved since the 2020 ceasefire, remains fragile, and armed conflict has directly damaged research infrastructure and disrupted academic calendars. These factors are not independent: political instability deters foreign investment in digital infrastructure, which limits AI deployment, which reduces the domestic demand for AI skills, which accelerates brain drain, which further weakens institutions.

The data ecosystem presents a second set of interconnected barriers. The absence of a data protection law prevents the data sharing that would enable AI development. The lack of data standards makes it difficult to integrate datasets from different sources. The limited digitization of government records means that much potentially useful data exists only in paper form. Moreover, the high cost of internet access excludes potential data contributors and users in lower-income populations.

b. **Prioritized Research Directions**

Given these constraints, we argue that AI research in Libya should prioritize domains where satellite or remote sensing data can substitute for ground-truth data collection, where the research questions are specific to Libya and unlikely to be addressed by international

researchers, and where the results can directly inform policy or operational decisions. The environmental monitoring and conflict impact assessment work described in one of the authors' ongoing projects summarized in this survey exemplifies all three criteria.

Specific research priorities include the expansion of conflict-vegetation modeling using multi-sensor satellite data (Sentinel-1 radar, Sentinel-2 optical, and Landsat thermal), the development of Libya-specific crop yield prediction models, and the scaling of the MLACD approach to all at-risk archaeological sites. In each case, the research would generate both scientific publications and datasets that would enable further work. A second priority area is the development of Libyan Arabic NLP resources, including a transcribed speech corpus, a written text corpus, and benchmark tasks for dialect identification and machine translation. These resources would enable both linguistic research and practical applications in education and government services.

c. **Policy Priorities**

The most urgent policy priority is the adoption of a data protection law that enables responsible data sharing while protecting individual privacy. Without such a law, the data ecosystem will remain fragmented and AI development will be confined to domains that can generate their own data. The second priority is the establishment of university AI centers of excellence with guaranteed international bandwidth, dedicated computational resources, and stable funding for multi-year research programs. The third priority is the creation of structured programs to engage the Libyan AI diaspora in domestic research and training.

8. **Conclusion**

This survey has mapped an AI landscape characterized by a fundamental tension between potential and constraint. Libya possesses urgent problems that AI can address, researchers who are actively publishing in relevant domains, and a nascent policy framework that acknowledges the importance of AI for national development. At the same time, structural barriers in infrastructure, data, human capital, and governance create constraints that no single intervention can resolve.

The path forward requires coordinated action across multiple fronts: investment in digital infrastructure, adoption of enabling legislation, reform of university curricula, engagement of the diaspora, and support for domain-specific research that leverages Libya's unique data assets. The research described in one of the authors' ongoing projects summarized in this survey — using machine learning to analyze the impact of armed conflict on vegetation cover — represents exactly the kind of Libya-specific, policy-relevant AI research that can build the case for continued investment and demonstrate the value of AI for national development.

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الشكر والتقدير

التمويل: نعم ☒ لا ☐
 تضارب المصالح: نعم ☐ لا ☒
 توافر البيانات: نعم ☐ لا ☐

مساهمات المؤلفين:

ت	اسم المؤلف وإيميله	تصور وُفكرة الدراسة	جمع أو المساهمة في جمع البيانات	المساهمة في الدراسات السابقة	وضع منهجية الدراسة	إجراء التحليل (الجانب العملي)	تحليل البيانات	تفسير ومناقشة النتائج	الموافقة على النسخة النهائية
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