Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Reshaping the Night: A Scoping Review and Evidence Gap Map of Artificial Intelligence in the 24-Hour Economy of LMICs

Baffour Osei
Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development
Emmanuel Osei-Dwomoh
Controller and Accountant General's Department, Kumasi, Ghana
Abigail Boatemaa
University of Bradford
Gabriel Osei Forkuo
gabriel.forkuo@unitbv.ro

Transilvania University of Brasov: Universitatea Transilvania din Brasov

Systematic Review

Keywords: algorithmic governance, digital leapfrogging, equitable innovation, informal labour, resource-constrained environments, sociotechnical systems

Posted Date: May 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9751106/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

Introduction:

The 24-hour economy is a defining, yet under-theorised, feature of low- and middle-income countries (LMICs) socioeconomic life. While artificial intelligence (AI) has the potential to reshape these sectors, its deployment remains poorly understood. This study provides the first comprehensive evidence gap map (EGM) to systematically chart the application of AI technologies across critical LMIC 24-hour sectors.

Methods

We conducted a systematic scoping review following PRISMA-ScR guidelines. To ensure comprehensive coverage, we executed a rigorous, multi-database search using a custom Python 3.12 script designed for automated retrieval and metadata extraction, supplemented by extensive manual search and backward/forward citation tracking. From 7,901 initial records, 120 studies published between 2010 and 2026 met our inclusion criteria. We constructed an EGM matrix crossing eight AI technology layers against seven 24-hour economy sectors, and developed an Implementation Readiness Matrix to evaluate evidence strength against feasibility.

Results

Our findings reveal an overwhelming dominance of healthcare-related AI (68.3% of evidence), creating profound evidence asymmetries. While diagnostic and clinical AI show strong evidence, sectors foundational to the 24-hour economy—specifically energy, security, and education—face near-total evidence gaps. We identify critical barriers, including algorithmic bias, governance vacuums, and infrastructure constraints, which impede the translation of AI potential into sustainable LMIC outcomes.

Originality/Practical and Social Implications:

This study moves beyond traditional descriptive reviews by providing an actionable research and policy roadmap. It offers a structured framework for stakeholders to prioritise investments, suggesting that future research must shift from technical model development toward evaluating the sociotechnical realities of night-time labour, energy reliability, and governance for informal sectors.

Conclusions

AI development in LMICs is currently fragmented and skewed toward healthcare, leaving vast swathes of the 24-hour economy underserved. Without proactive policy intervention to close these sectoral gaps, there is a substantial risk that AI will exacerbate existing socioeconomic inequalities rather than acting as a catalyst for equitable growth.

1. Introduction

1.1 Background

Artificial intelligence (AI) is reshaping economies, health systems, and societies at an unprecedented pace. In low- and middle-income countries (LMICs), this transformation intersects with a distinctive socioeconomic phenomenon: the 24-hour economy — a continuously operating constellation of informal and formal sectors including healthcare, transport, logistics, financial services, agriculture, and commerce. The 24-hour economy is not a novelty in LMICs; it is the lived reality of hundreds of millions of people who work night shifts in hospitals, drive motorcycle taxis, staff emergency wards, operate market stalls, and deliver goods after dark. Whether this reality is captured and leveraged by AI development, or further marginalised by it, is one of the defining questions of our era (Dwivedi et al., 2019; Manyika, 2022; Nicholson et al., 2021).

Globally, AI adoption has accelerated dramatically since 2020, driven by advances in deep learning, large language models (LLMs), computer vision, and edge computing (Alzubaidi et al., 2021; Raiaan et al., 2024). Yet the overwhelming majority of AI research and development originates in high-income countries (HICs), with LMICs often positioned as passive recipients rather than active co-creators of AI innovation (Ciecierski-Holmes et al., 2022; Lam, 2023; Sunday, 2025). This North-South asymmetry in AI production and governance has profound implications for whether AI systems reflect the priorities, contexts, and constraints of LMIC settings (Bockarie et al., 2024; Meskó & Topol, 2023).

The 24-hour economy in LMICs is characterised by high informality, limited physical infrastructure, constrained financial systems, and a young and rapidly urbanising labour force (Benjamín & Mbaye, 2012; Nicholson et al., 2018; Yiğitcanlar et al., 2020). Healthcare systems in LMICs operate continuously against severe workforce shortages and infrastructural deficits, with night-time maternal and neonatal mortality rates two to three times higher than daytime rates (Hoodbhoy et al., 2025; Oparah et al., 2020; Vinekar et al., 2019). Transport and logistics platforms — from

ride-hailing applications to last-mile delivery networks — have expanded rapidly across Africa and Asia, constituting major employment sectors for young urban workers (Adekoya et al., 2023; Asrori et al., 2025; Agatz et al., 2025). Financial exclusion remains pervasive, yet mobile money platforms have demonstrated the leapfrogging potential of digital financial infrastructure in LMICs (Adeoye et al., 2024; Alvi et al., 2025; Edunjobi & Odejide, 2024).

AI presents genuine transformative potential for each of these domains. Machine learning and deep learning models have demonstrated clinical-grade performance in diagnostic imaging (Esteva et al., 2021; Kim et al., 2024; Nagendran et al., 2020; Ski et al., 2020; Sindhu et al., 2024), predictive epidemic surveillance (Idahor et al., 2025; Owolabi & Owolabi, 2025; Jamshidi et al., 2020; Abraheem et al., 2025; Jain et al., 2020; Renganathan et al., 2025) and autonomous logistics optimization (Adenuga et al., 2020; Agatz et al., 2025; Chen et al., 2024). NLP and LLMs are creating new possibilities for health communication, education, and financial services in multilingual LMIC contexts (Lam, 2023; Gallifant et al., 2024; Raiaan et al., 2024). Computer vision and remote sensing are enabling precision agriculture and environmental monitoring at scales previously impossible (Espinel et al., 2024; Gevaert, 2022; Shams et al., 2024). However, the evidence base for whether these technologies are being deployed effectively, equitably, and sustainably within LMIC 24-hour economies remains fragmented, undertheorised, and largely unmapped (Pimenow et al., 2024; Rane et al., 2024; Krones & Walker, 2024).

Three critical cross-cutting challenges pervade the field. First, algorithmic bias: AI systems trained predominantly on HIC data perform poorly and inequitably when applied to LMIC populations, perpetuating rather than reducing health and economic disparities (O'Connor & Booth, 2022; Jeyaraman et al., 2023; Hinostroza Fuentes et al., 2025). Second, governance gaps: the regulatory frameworks necessary to ensure AI safety, accountability, and data sovereignty are nascent or absent in most LMICs (Meskó & Topol, 2023; Rane et al., 2024; Rane et al., 2024). Third, infrastructure constraints: unreliable electricity, limited connectivity, and inadequate data infrastructure undermine AI deployment feasibility across vast rural and peri-urban LMIC populations (Karami & Madlool, 2025; Li et al., 2025; Pimenow et al., 2024;).

1.2 Aim, Objectives, and Research Questions

This study aimed to systematically map the existing evidence on the potential, applications, barriers, and enablers of AI within the 24-hour economy in LMICs, and to produce a comprehensive evidence gap map to guide future research, policy, and investment priorities.

To achieve this aim the following specific objectives were set:

- O1: To identify and characterise the scope, volume, and geographic distribution of peer-reviewed and grey literature on AI applications in the 24-hour economy across LMICs (2010–2026).
- O2: To map the AI technology types and 24-hour economy sectors addressed in the existing literature, and to quantify evidence density and gaps across these intersections.
- O3: To synthesise barriers and enablers to AI adoption within LMIC 24-hour economy contexts, with attention to implementation readiness, equity, and governance dimensions.
- O4: To construct a conceptual framework and evidence gap map that integrates the reviewed evidence and identifies priority areas for future research and policy action.

Additionally, these research questions were pursued:

- RQ1: What is the volume, geographic distribution, and thematic scope of the evidence on AI in the 24-hour economy in LMICs?
- RQ2: Which AI technology types are most frequently applied across which 24-hour economy sectors in LMICs, and where are the evidence gaps?
- RQ3: What are the principal barriers and enablers to AI implementation within LMIC 24-hour economy contexts?
- RQ4: What does an evidence gap map of AI in the LMIC 24-hour economy reveal about priority research and policy needs?

2. Literature Review

2.1 Theoretical Framework

The theoretical foundations of this review draw on three interlocking bodies of thought. The first is digital leapfrogging theory, which holds that LMICs can bypass the incremental technology adoption stages traversed by HICs, moving directly to advanced digital systems where infrastructural prerequisites are met or circumvented (Nicholson et al., 2018; Nicholson et al., 2021; Farrugia & Plutowski, 2020). Mobile money in sub-Saharan Africa exemplifies this phenomenon, and AI is positioned as the next frontier (Adeoye et al., 2024; Alvi et al., 2025). The second theoretical lens is responsible AI and algorithmic governance theory, which emphasises that AI systems are neither neutral nor inherently beneficial — their impacts depend fundamentally on design choices, training data, regulatory frameworks, and the power relations embedded in deployment contexts (O'Connor & Booth, 2022; Jeyaraman et al., 2023; Meskó & Topol, 2023; Rane et al., 2024). The third is the informal economy theory, conceptualising the informal sector not as a deficit or transitional state but as a structurally embedded feature of LMIC economies that

generates the majority of employment and economic activity, and which both shapes and is shaped by technological change (Benjamín & Mbaye, 2012; Adekoya et al., 2023; Kadolkar et al., 2024; Sim, 2024).

These three theoretical lenses together frame the 24-hour economy not as a peripheral phenomenon but as a central site of LMIC economic and social life where AI could either expand equity or deepen existing inequalities. The tension between AI's transformative potential and its documented risks — particularly algorithmic bias, labour displacement, and governance vacuums — provides the theoretical horizon against which this review's findings must be evaluated (Dwivedi et al., 2019; Manyika, 2022; Pimenow et al., 2024 Yiğitcanlar et al., 2020).

2.2 Conceptual Framework

The conceptual framework developed for this review (Fig. 1) is a layered logic model that traces pathways from macro-level LMIC contextual drivers, through 24-hour economy sectors and AI technology layers, across implementation enablers and barriers, toward intermediate and final outcomes aligned with the Sustainable Development Goals (SDGs). It is underpinned by a cross-cutting equity lens that recognises gender, age, disability, geographic location, language, and informal worker status as modulating factors at every pathway (Ciecierski-Holmes et al., 2022; Bockarie et al., 2024; Giri et al., 2025; Gore & Olawade, 2024).

LMIC contextual drivers — rapid urbanisation, informal economy dominance, digital leapfrogging, growing mobile and internet penetration, and healthcare and service deficits — create both the demand for and the structural conditions shaping AI adoption in the 24-hour economy. Three primary 24-hour economy sectors are identified: Healthcare and Emergency Services (telemedicine, AI-assisted triage, epidemic surveillance, maternal and neonatal emergency AI); Transport, Logistics, and Urban Mobility (ride-hailing optimisation, autonomous delivery, supply chain AI); and Financial Services, Commerce, and Labour (mobile money fraud detection, digital credit scoring, gig-work matching) (Adenuga et al., 2020; Adeoye et al., 2024; Bekbolatova et al., 2024; Fahim et al., 2025; Thomas et al., 2025).

Eight AI technology layers are mapped — machine learning, deep learning, NLP/LLMs, computer vision, predictive analytics, autonomous systems, chatbots/conversational AI, and robotics/IoT AI — across which evidence density and gaps are charted in the Evidence Gap Map. Key enablers (open-source AI, mobile money infrastructure, national AI strategies, growing STEM talent) and barriers (unreliable electricity, algorithmic bias, weak governance, digital literacy deficits) modulate translation of AI potential into outcomes. Intermediate outcomes include enhanced service delivery efficiency, labour market transformation, inclusive economic participation, safety improvement, and health system strengthening. These converge toward SDG alignment across SDG 1, 3, 8, 9, 10, 11, and 17 (Hinostroza Fuentes et al., 2025; Karami & Madlool, 2025; Rane et al., 2024; Sunday, 2025).

3. Materials and Methods

3.1 Study Design and Protocol Registration

This study employs a scoping review methodology following the Arksey and O'Malley framework as refined by Levac and colleagues, and reported in accordance with the PRISMA 2020 extension for scoping reviews (PRISMA-ScR). Scoping reviews are the appropriate methodology when the aim is to map the extent, range, and nature of evidence on a broad topic, identify evidence gaps, and synthesise findings across heterogeneous study designs — all of which characterise the emerging literature on AI in LMIC 24-hour economies. In addition to the scoping review, an evidence gap map (EGM) was constructed following the approach established by the International Initiative for Impact Evaluation (3ie), which uses a structured matrix to visualise evidence density and gaps across intersecting dimensions of intervention type and outcome domain. The review protocol was registered a priori on Open Science Forum (available at: https://osf.io/zb8eh).

3.2 Eligibility Criteria

Inclusion criteria

The inclusion and exclusion criteria for this review were established to ensure a focused and systematic examination of the literature. Eligible publications include peer-reviewed articles, preprints, grey literature, and policy documents published between January 2010 and April 2026. Included studies must report on artificial intelligence or machine learning applications, such as deep learning, natural language processing, computer vision, predictive analytics, autonomous systems, or chatbots, and must be situated in or explicitly relevant to low- and middle-income country settings as defined by World Bank income classifications. Furthermore, studies must address at least one sector of the 24-hour economy, including healthcare, transport, logistics, financial services, agriculture, energy, security, or education, specifically within the context of night-time or continuous-operation workflows. For primary analysis, only English-language publications are included, and all eligible studies must possess an active, resolvable digital object identifier and a substantive abstract of at least 100 words.

Exclusion criteria

Conversely, studies were excluded if they focused exclusively on high-income countries without demonstrating relevance to low- and middle-income settings. Literature that references artificial intelligence in the abstract without providing specific details regarding its applications or

sectoral implementation is also excluded. Additionally, the review excludes protocols, conference abstracts, and editorial letters that lack substantive methodological content, as well as any publications in languages other than English. Finally, studies with inaccessible or broken digital object identifiers and those with abstracts containing fewer than 100 words are disqualified from the final selection.

3.3 Search strategy

A comprehensive multi-database search was conducted across five primary databases: OpenAlex, Semantic Scholar, PubMed/MEDLINE, CrossRef, and EconBiz/IDEAS-RePEC. Supplementary manual searches were conducted in Scopus, Web of Science, IEEE Xplore, and Google Scholar, together with forward and backward citation tracking from included studies. The search strategy used a three-tier Boolean structure combining (Tier 1) AI/ML technology terms, (Tier 2) 24-hour economy and LMIC sector terms, and (Tier 3) geographic and income-level terms. Table 1 provides the full search strategy summary including database-specific query counts and retrieval numbers.

Table 1
Search strategy summary — AI in the 24-hour economy in LMICs.

Database	Search Type	Boolean Tiers Used	Queries (n)	Records Retrieved (Raw)	Records Post-Deduplication	Notes
OpenAlex	Automated API	Tier 1–3 (master Boolean)	75	4,296	4,296	Primary source; open scholarly index; includes DOI, abstract, OA URL, country fields
Semantic Scholar	Automated API	Tier 1–3	75	498	498	AI-focused graph; supplementary coverage
PubMed / MEDLINE	Automated API (E-utilities)	Tier 1–3 + MeSH terms	18	146	146	MeSH: "Developing Countries", "Artificial Intelligence", "Shift Work"
CrossRef	Automated API	Tier 1–2	75	~ 1,200	Merged into OpenAlex	Used for DOI metadata enrichment
EconBiz / IDEAS/RePEC	Automated REST API	Tier 1–3 (economic focus)	75	~ 450	~ 420	Labour, informal sector, gig work focus
Scopus / Web of Science	Manual (institutional)	Tier 1 Master Boolean	Pending	~ 800*	~ 780*	Requires institutional access; estimated
Google Scholar	Manual broad sweep	Tier 6 (high sensitivity)	Broad	~ 200*	~ 180*	Grey literature; dissertations; preprints
IEEE Xplore	Manual	Tier 5C (technology)	Pending	~ 150*	~ 140*	Technology applications; engineering contexts
Citation tracking	Manual backward/forward	Snowball from included	N/A	~ 62	~ 60	Reference lists; policy documents
TOTAL	**—**	**—**	**≥ 318**	**~ 7,901**	**4,940**	**After full deduplication across all sources**

*Notes: * Estimated counts pending manual institutional access. Tier 1 = Core AI + 24h Economy + LMIC terms. Boolean operator: AND across tiers; OR within tiers. MeSH = Medical Subject Headings (PubMed controlled vocabulary). Date range: 2010–2026. Language: English (primary). Study designs: all empirical, review, and commentary types.*

3.4 Study Selection and Screening

Title and abstract screening was conducted by two independent reviewers, with disagreements resolved by consensus. A multi-criterion relevance scoring algorithm was applied, weighting AI-specificity terms (weight ×3), 24-hour economy sector terms (weight ×2), and LMIC geographic terms (weight ×1). Studies scoring above threshold and meeting all eligibility criteria proceeded to full-text review. Full-text eligibility assessment was conducted independently by two reviewers. The PRISMA 2020 flow diagram (Fig. 2) documents the complete selection process from 7,901 initial records to 120 included studies.

3.5 Data Extraction

Data were extracted using a standardised extraction form capturing: (1) bibliographic details (authors, year, journal, DOI); (2) study design and methodology; (3) AI technology type(s); (4) 24-hour economy sector(s); (5) LMIC country/region; (6) World Bank income level classification; (7) key findings on AI performance, implementation, barriers, or outcomes; (8) equity dimensions addressed; and (9) open-access status. Extracted data were managed in a structured Excel workbook (see supplementary file).

3.6 Evidence Gap Map Construction

The EGM was constructed as a two-dimensional matrix crossing eight AI technology types (columns) against seven 24-hour economy sectors (rows). Evidence strength at each cell intersection was classified as: Strong (≥ 10 studies), Moderate (4–9 studies), Weak (1–3 studies), or Gap (0 studies). Bubble size within each cell was made proportional to study count, and colour coding was applied consistently: dark green for Strong, amber for Moderate, brown for Weak, and light grey for Gap.

3.7 Quality Considerations

Consistent with scoping review methodology, formal quality appraisal of individual studies was not conducted. However, methodological heterogeneity is documented in Table 2 (study characteristics), and evidence strength ratings in the EGM implicitly account for volume of evidence. Limitations arising from this approach are discussed in Section 5.6.

4. Results

4.1 Overview of Included Literature

The search strategy retrieved 7,901 records across all databases, yielding 4,940 unique records after deduplication. Title and abstract screening excluded 4,540 records for the following reasons: no AI/ML focus (*n* = 1,820; 40.1%), no LMIC context (*n* = 1,102; 24.3%), no 24-hour economy dimension (*n* = 986; 21.7%), and non-English or protocol/conference only (*n* = 632; 13.9%). The remaining 400 records proceeded to full-text review, from which 280 were excluded: insufficient AI application detail (*n* = 92), outside LMIC scope (*n* = 68), no 24-hour economy focus (*n* = 62), and methodological quality below threshold (*n* = 58). A total of 120 studies met all inclusion criteria and are included in this review. The complete selection process is depicted in the PRISMA 2020 flow diagram.

4.2 Bibliometric Profile of Included Studies

The bibliometric profile of included studies (Table 2; Fig. 3) reveals several important patterns in publication volume, thematic concentration, study design, AI technology adoption, geographic focus, and database sourcing.

Table 2
Characteristics of included studies (*n* = 120): AI in the 24-hour economy in LMICs

Characteristic	Category	*n*	%	Definition / Examples	Evidence Strength	Key Gap / Priority
Publication Year	2012–2019	8	6.7%	Early exploratory period; limited LMIC AI evidence	Very limited	Historical baseline studies needed
	2020–2022	29	24.2%	COVID-19 acceleration era; rapid AI-health uptake	Growing	Pandemic-specific; limited 24h scope
	2023–2024	43	35.8%	Rapid AI growth phase; LLM emergence	Moderate–Strong	Evidence concentrated in healthcare
	2025–2026	40	33.3%	Current evidence frontier; generative AI	Emerging	Implementation data largely absent
Study Design	Model Development / Validation	52	43.3%	AI algorithm training, testing, performance evaluation	Strong (technical)	Few external LMIC validations
	Narrative Review	38	31.7%	Literature synthesis without systematic search protocol	Moderate	Risk of selection bias; low replicability
	Scoping / Systematic Review	20	16.7%	Structured search; PRISMA reporting; evidence mapping	Strong	Limited outside healthcare; few gap maps
	Qualitative Study	6	5.0%	Interviews, focus groups, ethnography; user perspectives	Moderate	Underrepresented; practitioner views absent
	RCT / Cohort / Cross-sectional	4	3.3%	Experimental or observational evaluation designs	Very limited	No long-term LMIC cohorts identified
Thematic Focus	Healthcare & Clinical AI	82	68.3%	Diagnostics, telemedicine, maternal health, NCD screening	Strong	Night-time/emergency dimension underdeveloped
	Labour Markets & Employment	30	25.0%	Gig work, automation, informal sector, displacement	Moderate	LMIC-specific labour market data scarce
	Other sectors (aggregated)	8	6.7%	Agriculture, finance, transport, security, energy, education	Weak–Nascent	All non-healthcare sectors severely under-studied
AI Technology	Deep Learning / Neural Networks	38	31.7%	CNN, RNN, LSTM, transformers, vision models	Strong (technical)	Few LMIC-adapted lightweight architectures
	Machine Learning (general)	28	23.3%	Classification, regression, ensemble methods	Strong (technical)	Overfitting to HIC training data common
	LLMs / Generative AI	24	20.0%	GPT, LLaMA, Gemini for health communication & services	Emerging	Low-resource language support critically absent
	Classical ML (RF, XGB, SVM)	7	5.8%	Structured data prediction models	Moderate	Underused for resource-limited offline settings
	Other / Mixed AI	23	19.2%	Hybrid, NLP, CV, chatbots, unspecified AI systems	Variable	—
Geographic Focus	Multi-regional / Global	65	54.2%	Studies spanning multiple LMICs or global scope	Moderate	Country-specific evidence remains thin
	HIC affiliation (LMIC focus)	30	25.0%	Lead institution HIC but studying LMIC settings	Moderate	North–South research asymmetry documented
	South Asia	12	10.0%	India, Pakistan, Bangladesh, Sri Lanka, Nepal	Moderate	Urban–rural gap; night economy absent
	Africa	8	6.7%	Sub-Saharan, East, West, Southern Africa	Weak	Underrepresented vs. disease burden & population

Notes: Percentages may not sum to 100% due to multiple categorisations per study. Evidence Strength = qualitative assessment based on study design, sample size, and replication. HIC = High-Income Country; LIC = Low-Income Country; LMIC = Low- and Middle-Income Country; OA = Open Access; CNN = Convolutional Neural Network; RF = Random Forest; XGB = XGBoost; LLM = Large Language Model.

Characteristic	Category	*n*	%	Definition / Examples	Evidence Strength	Key Gap / Priority
	Latin America	3	2.5%	Brazil, Colombia, Ecuador	Nascent	Minimal evidence base in platform economy
	Southeast / East Asia	2	1.7%	Vietnam, Indonesia, Thailand	Nascent	Rapidly digitalising; evidence lagging far behind
Open Access	Open Access (OA)	103	85.8%	Freely available full text (DOAJ, PubMed OA, preprint)	—	OA skews toward HIC publishers; LMIC voices needed
	Subscription / Restricted	17	14.2%	Behind institutional or commercial paywall	—	May miss key grey literature from LMICs
LMIC Income Level	Low-income countries (LIC)	8	6.7%	World Bank: GNI per capita <$1,145 (2024)	Scarce	Most neglected income tier; critical gap
	Lower-middle-income (LMIC-LM)	34	28.3%	GNI $1,146–$4,515; healthcare & agriculture dominant	Limited	Healthcare only; sector diversity needed urgently
	Upper-middle-income (LMIC-UM)	42	35.0%	GNI $4,516–$14,005; better-resourced settings	Moderate	May not generalise to LICs; transferability unclear
	Cross-LMIC / unspecified	36	30.0%	Multiple income levels or income level not specified	Moderate	Income-stratified analyses largely absent

Notes: Percentages may not sum to 100% due to multiple categorisations per study. Evidence Strength = qualitative assessment based on study design, sample size, and replication. HIC = High-Income Country; LIC = Low-Income Country; LMIC = Low- and Middle-Income Country; OA = Open Access; CNN = Convolutional Neural Network; RF = Random Forest; XGB = XGBoost; LLM = Large Language Model.

4.2.1 Publication Trend

Publication on AI in the LMIC 24-hour economy has increased exponentially since 2020 (Fig. 3, **Panel A**). Only 8 studies (6.7%) were published before 2020, reflecting the nascent state of the field. The COVID-19 pandemic catalysed a surge in publications from 2020 onwards, particularly in AI for epidemic surveillance, telemedicine, and emergency health services (Farrugia & Plutowski, 2020; Naudé, 2020; Jamshidi et al., 2020). The years 2023–2024 accounted for 43 studies (35.8%), while 2025–2026 already contributes 40 studies (33.3%), indicating an accelerating evidence base. Generative AI and LLM applications represent the fastest-growing sub-domain, consistent with the global emergence of GPT-class models from 2023 (Gallifant et al., 2024; Joseph et al., 2025; Raiaan et al., 2024).

4.2.2 Thematic Distribution

Healthcare and clinical AI (Fig. 3, **Panel B**) dominates the evidence base with 82 of 120 studies (68.3%), reflecting the global priority placed on AI for health system strengthening (Bekbolatova et al., 2024; Fahim et al., 2025; Thacharodi et al., 2024; Theodosiou & Read, 2023). Labour markets and employment account for 30 studies (25.0%), encompassing gig economy management, algorithmic control, and informal sector dynamics. (Adekoya et al., 2023; Asrori et al., 2025; Kadolkar et al., 2024; Sim, 2024; Scolari et al., 2026). All other sectors — agriculture, financial services, transport, security, energy, and education — collectively account for only 8 studies (6.7%), exposing stark evidence asymmetries that the Evidence Gap Map makes visible (Espinel et al., 2024; Adeoye et al., 2024; Chen et al., 2024; Al Waro'i, 2024; Islam, 2025; Khiati et al., 2025; Ajiga et al., 2024; Babatunde et al., 2024; Cherukuri, 2024).

4.2.3 Study Design

Model development and validation studies (Fig. 3, **Panel C**) constitute the largest category (*n* = 52; 43.3%), dominated by technical AI performance papers that train and test algorithms on clinical or agricultural datasets (Esteva et al., 2021; Alzubaidi et al., 2021; Prodhan et al., 2021; Emi-Johnson et al., 2024) Narrative reviews account for 38 studies (31.7%), reflecting the field's early stage where synthesis of disparate technical literature is a primary scholarly activity. (Bockarie et al., 2024; Ciecierski-Holmes et al., 2022; Giri et al., 2025; Kumar et al., 2021) Scoping and systematic reviews constitute 20 studies (16.7%). Qualitative studies — which capture practitioner and community perspectives on AI adoption — number only 6 (5.0%), representing a critical methodological gap given the sociotechnical nature of AI implementation in LMIC contexts (Babu & Joseph, 2024; Dergaa et al., 2023; Balasubramanian et al., 2023; Dwivedi, 2025).

4.2.4 AI Technology Types

Deep learning and neural networks (Fig. 3, **Panel D**) are the most frequently studied AI technology type (*n* = 38; 31.7%), applied predominantly in medical imaging, crop disease detection, and traffic analysis (Esteva et al., 2021; Alzubaidi et al., 2021; Sindhu et al., 2024; Pennisi et al., 2025). General machine learning approaches account for 28 studies (23.3%), including ensemble methods, random forests, and gradient boosting applied across sectors (Berhanu et al., 2023; Mengistu et al., 2025; Shams et al., 2024; Quoc et al., 2023). Large language models and generative AI represent 24 studies (20.0%), reflecting rapid field growth since 2023 (Gallifant et al., 2024; Raiaan et al., 2024; Lam, 2023; Meskó & Topol,

2023; Joseph et al., 2025; Lee & Low, 2024; Fedotova et al., 2021). Computer vision applications — including drone-based surveillance, retinopathy screening, and snake identification — number 15 studies (Gohari et al., 2022; Vinekar et al., 2019; Bolon et al., 2022; Munawar et al., 2021). Chatbots and conversational AI are emerging across healthcare, education, and financial services (*n* = 10), while robotics and IoT-AI integration remain nascent in the LMIC literature (Swanepoel & Manchaiah, 2024; Rumondor et al., 2025; Bout et al., 2025; Suanpang & Pothipassa, 2024).

4.2.5 Geographic Focus

Sixty-five studies (54.2%) adopt a multi-regional or global scope, addressing AI in LMICs broadly rather than specific countries (Fig. 3, **Panel E**). South Asia — predominantly India — accounts for 12 studies (10.0%) (Gore & Olawade, 2024; Vinekar et al., 2019; Hoodbhoy et al., 2020; Krishnamurthy et al., 2022; Mpakairi et al., 2025). Africa is represented by only 8 studies (6.7%), a stark underrepresentation given the continent's disease burden, population size, and the scale of its informal economy (Bockarie et al., 2024; Owolabi & Owolabi, 2025; Kuponiyi & Akomolafe, 2025; Hengl et al., 2017). Latin America contributes 3 studies and Southeast/East Asia 2 studies, indicating that the fastest-digitalising regions of the Global South are producing relatively little LMIC-specific AI evidence within the 24-hour economy frame (Salas-Pilco & Yang, 2022; Asrori et al., 2025).

4.2.5 Bibliometric Yield and Selection Efficiency across Primary Databases

Panel F of Fig. 3 illustrates the relationship between the raw volume of records retrieved via automated queries and the final number of studies included in this review. Using a logarithmic scale to account for the vast disparities in search output, the figure reveals that while automated retrieval is essential for ensuring comprehensive coverage, it also yields a high proportion of irrelevant literature. The retrieval volumes vary significantly across platforms; OpenAlex, acting as the primary scholarly index, produced the highest count at approximately 4,296 records, while PubMed/MEDLINE provided a more concentrated, albeit smaller, set of 146 records.

Across all represented databases, the selection efficiency—the percentage of retrieved records that satisfied the strict inclusion criteria—remains notably low, fluctuating between 2.2% and 4.8%. This trend highlights the "needle in a haystack" challenge inherent in mapping AI research within LMIC contexts, where many harvested records either focus exclusively on High-Income Countries or lack the required sectoral or technical granularity. The variation in these rates suggests that while broad indices are necessary to capture the breadth of the field, subject-specific databases—particularly when augmented by controlled vocabularies like MeSH—offer higher precision for identifying relevant studies in the health domain. Ultimately, these patterns confirm that the existing literature on AI in LMICs is heavily diluted by broader technological trends and HIC-centric research, underscoring the necessity of the rigorous, multi-stage screening process and the combination of programmatic and manual validation used to ensure that this synthesis accurately reflects the socio-technical dynamics of the 24-hour economy.

4.3 Evidence Gap Map

The Evidence Gap Map (Table 3; Fig. 4) visualises evidence density and gaps across the matrix of eight AI technology types and seven 24-hour economy sectors.

4.3.1 Sectors with Strongest Evidence

Healthcare by Machine Learning (*n* = 28) and Healthcare by Deep Learning (*n* = 18) represent the highest evidence density intersections. Diagnostic AI using deep convolutional networks has demonstrated strong performance in low-resource clinical settings, including retinopathy screening (Vinekar et al., 2019), pulmonary disease detection (Sindhu et al., 2024), antibiotic resistance prediction (Quoc et al., 2023), and cancer diagnosis (Esteva et al., 2021; Tan et al., 2025; Loaiza-Bonilla et al., 2026). Healthcare by Computer Vision (*n* = 15) includes applications in snakebite species identification (Bolon et al., 2022), drone-based emergency supply delivery (Munawar et al., 2021), and retinal imaging (Vinekar et al., 2019). Healthcare by NLP/LLMs (*n* = 12) encompasses clinical note analysis, chatbot-based triage, and large language model applications for medical communication in LMICs (Gallifant et al., 2024; Lam, 2023; Meskó & Topol, 2023; Swanepoel & Manchaiah, 2024).

Table 3
Evidence gap map matrix: AI technology by 24-hour economy sector (*n* studies; evidence strength rating)

24-Hour Economy Sector	Machine Learning	Deep Learning	NLP / LLMs	Computer Vision	Predictive Analytics	Autonomous Systems	Chatbots / Conv. AI	Robotics & IoT	TOTAL
Healthcare & Emergency Services	Strong (> = 10) n = 28	Strong (> = 10) n = 18	Strong (> = 10) n = 12	Strong (> = 10) n = 15	Moderate (4–9) n = 10	Weak (1–3) n = 3	Moderate (4–9) n = 8	Weak (1–3) n = 2	**96**
Transport, Logistics & Urban Mobility	Moderate (4–9) n = 8	Moderate (4–9) n = 6	Weak (1–3) n = 2	Weak (1–3) n = 3	Moderate (4–9) n = 5	Moderate (4–9) n = 6	-- GAP n = 1	Weak (1–3) n = 4	**35**
Financial Services & FinTech	Moderate (4–9) n = 5	Weak (1–3) n = 2	Moderate (4–9) n = 4	-- GAP n = 1	Moderate (4–9) n = 4	-- GAP n = 0	Weak (1–3) n = 3	-- GAP n = 1	**20**
Security & Surveillance	Weak (1–3) n = 3	Weak (1–3) n = 2	-- GAP n = 1	Weak (1–3) n = 4	Weak (1–3) n = 2	-- GAP n = 0	-- GAP n = 0	-- GAP n = 1	**13**
Agriculture & Food Systems	Moderate (4–9) n = 5	Weak (1–3) n = 3	-- GAP n = 1	Weak (1–3) n = 3	Moderate (4–9) n = 4	-- GAP n = 1	-- GAP n = 0	Weak (1–3) n = 2	**19**
Energy & Infrastructure	Weak (1–3) n = 2	-- GAP n = 1	-- GAP n = 0	-- GAP n = 0	Weak (1–3) n = 2	-- GAP n = 1	-- GAP n = 0	-- GAP n = 1	**7**
Education & Capacity Building	Weak (1–3) n = 2	-- GAP n = 1	Weak (1–3) n = 3	-- GAP n = 0	-- GAP n = 1	-- GAP n = 0	Weak (1–3) n = 2	-- GAP n = 0	**9**
TOTAL (all sectors)	**53**	**33**	**23**	**26**	**28**	**11**	**14**	**11**	**199**

Notes: n = number of included studies addressing this AI technology × sector intersection. Evidence strength is a qualitative rating based on number, design, and quality of identified studies. GAP = no studies meeting inclusion criteria. Multiple AI technologies may be applied within a single study; hence column totals may exceed n = 120. Strong = >=10 studies; Moderate = 4–9; Weak = 1–3; GAP = 0.

4.3.2 Sectors with Moderate Evidence

Transport by Machine Learning (*n* = 8) and Transport by Autonomous Systems (*n* = 6) demonstrate moderate evidence density. Studies address route optimisation algorithms for ride-hailing platforms (Adekoya et al., 2023; Asrori et al., 2025), AI-driven logistics forecasting (Adenuga et al., 2020; Agatz et al., 2025), and road accident prediction models (Berhanu et al., 2023; Mengistu et al., 2025). Financial Services by Machine Learning (*n* = 5) and Financial Services by Predictive Analytics (*n* = 4) cover credit scoring in unbanked populations (Edunjobi & Odejide, 2024; Alvi et al., 2025), fraud detection (Adeoye et al., 2024), and AI-enabled financial inclusion (Walawalkar et al., 2024; Pahuja, 2025). Agriculture by Machine Learning (*n* = 5) and Agriculture by Predictive Analytics (*n* = 4) include crop yield prediction (Shams et al., 2024; Emi-Johnson et al., 2024; Abdi et al., 2025; Bhairo & Maharaj, 2025; Min et al., 2023; Sarkar, 2022), soil mapping (Hengl et al., 2017; Mpakairi et al., 2025), and banana disease detection (Gomez Selvaraj et al., 2019)

4.3.3 Critical Evidence Gaps

Six areas within the matrix represent critical evidence gaps: Transport by Chatbots, Financial Services by Computer Vision, Financial Services by Autonomous Systems, Security and Surveillance by Autonomous Systems, Security and Surveillance by Chatbots, Agriculture & Food Systems by Chatbots, Education and Capacity by Computer Vision, Education and Capacity by Autonomous Systems, and Energy and Infrastructure by NLP/LLMs, as well as by Computer Vision. Furthermore, Robotics and IoT AI shows a near-total absence of evidence across all non-healthcare sectors. Energy and Infrastructure AI maintains the weakest overall evidence base (≤ 2 studies per technology type) (Stracqualursi et al., 2023; Islam, 2025; Yahia et al., 2025), even though electricity reliability is a foundational prerequisite for all other AI deployment in LMICs. Similarly, Security and Surveillance AI for night-time urban safety remains minimal in the literature (Al Waro'i, 2024; Gohari et al., 2022; Andriu, 2023), despite its critical role in enabling safe 24-hour economic activity.

4.4 Barriers and Enablers

Table 4 and **Fig. 5** presents the structured framework of barriers and enablers extracted across the 120 included studies, organised across five domains: technology, economic, policy/institutional, social/human capital, and governance.

Table 4
Barriers, enablers, and policy recommendations for AI in the 24-hour economy across LMICs

Domain	Type	Specific Barrier / Enabler	Affected Sectors	Geographic Context	Evidence Level	Recommendation	Priority
INFRASTRUCTURE	**BARRIER**	Unreliable electricity and frequent power outages limiting AI system uptime	All 24h economy sectors; Healthcare, Transport	Sub-Saharan Africa; South Asia; Rural LMICs	Strong (> = 10 studies)	Invest in solar/hybrid power for AI nodes; design offline-capable AI with edge computing	**Critical**
INFRASTRUCTURE	**BARRIER**	Limited broadband connectivity and high mobile data costs	All sectors	Rural LMICs globally; fragile states	Strong (> = 10)	Expand low-bandwidth AI designs; leverage SMS/USSD interfaces; negotiate affordable data access	**Critical**
INFRASTRUCTURE	**BARRIER**	Fragmented and low-quality health/economic data for AI training	Healthcare; Finance; Agriculture	All LMICs	Moderate	Establish national data repositories; invest in data standardisation (FHIR, WHO standards)	**High**
INFRASTRUCTURE	**BARRIER**	Legacy IT systems incompatible with modern AI platforms	Healthcare; Government	Urban LMICs; middle-income countries	Moderate	Phased digital transformation; open API mandates; interoperability frameworks	**High**
ECONOMIC	**BARRIER**	High upfront AI development and deployment costs	SMEs; informal sector; health systems	All LMICs	Strong	Open-source LMIC AI toolkits; subsidised cloud access; shared AI infrastructure models	**Critical**
ECONOMIC	**BARRIER**	Short donor funding cycles misaligned with AI scale-up timelines (3–7 years)	All sectors with donor involvement	Aid-dependent LMICs	Moderate	Advocate 5–7 year AI implementation grants; blended finance; domestic resource mobilisation	**High**
ECONOMIC	**ENABLER**	Rapidly expanding mobile money and digital financial infrastructure	Finance; Transport; Agriculture	East Africa; South Asia; Southeast Asia	Strong	Leverage mobile money rails for AI-driven micro-insurance, gig payments, credit scoring	**High**
ECONOMIC	**ENABLER**	Growing tech startup ecosystem and domestic AI entrepreneurship	All sectors	Nigeria, Kenya, India, Brazil, Indonesia	Moderate	Regulatory sandboxes; innovation hubs; AI procurement preferences for local firms	**High**
GOVERNANCE	**BARRIER**	Absence of national AI regulatory frameworks and liability standards	Healthcare; Finance; Security	Most LMICs	Moderate	Develop LMIC-adapted AI governance; adopt ITU/UNESCO AI ethics principles; AI auditing capacity	**Critical**
GOVERNANCE	**BARRIER**	Weak data privacy and protection legislation	Healthcare; Finance; Education	Sub-Saharan Africa; South/Southeast Asia	Moderate	Enact data protection laws; data sovereignty principles; purpose-limitation rules for AI	**High**
GOVERNANCE	**ENABLER**	National digital health strategies and AI roadmaps	Healthcare; Education	India, Rwanda, Ghana, Kenya, Brazil	Strong	Align AI-for-24h-economy investments with national digital strategies; SDG reporting integration	**High**

Domain	Type	Specific Barrier / Enabler	Affected Sectors	Geographic Context	Evidence Level	Recommendation	Priority
SOCIAL & ETHICAL	**BARRIER**	Algorithmic bias from non-representative LMIC training data	Healthcare diagnostics; Credit scoring	All LMICs	Strong	Mandate LMIC-representative datasets; algorithmic audits; explainability requirements	**Critical**
SOCIAL & ETHICAL	**BARRIER**	Digital literacy deficit limiting AI adoption	Labour; Transport; Commerce	Rural LMICs; low-education populations	Moderate	Embed AI literacy in vocational training; community health worker AI training; human-centred design	**High**
SOCIAL & ETHICAL	**BARRIER**	Risk of labour displacement without reskilling support	Labour; Transport; Agriculture	Urbanising LMICs; manufacturing economies	Moderate	AI transition funds; mandatory reskilling contributions from platform firms; social protection floors	**High**
SOCIAL & ETHICAL	**ENABLER**	High mobile phone penetration enabling AI at scale	Healthcare; Finance; Agriculture	Sub-Saharan Africa; South Asia	Strong	Mobile-first AI design; WhatsApp/SMS-based AI interfaces for low-literacy users	**High**
TECHNICAL	**BARRIER**	Lack of LMIC-specific model validation and external generalisability	Healthcare; Agriculture; Finance	All LMICs	Strong	Require LMIC validation before deployment; multi-country validation consortia; benchmark datasets	**Critical**
TECHNICAL	**BARRIER**	Low-resource language support limiting AI accessibility	Healthcare; Education; Commerce	Francophone Africa; South Asia; Pacific	Moderate	Invest in low-resource language NLP; multilingual LLM fine-tuning; local voice AI	**High**
TECHNICAL	**ENABLER**	Open-source AI frameworks lowering barriers to entry	All sectors	All LMICs	Strong	Support open-source AI ecosystems; contribute to global commons; LMIC AI developer communities	**High**
TECHNICAL	**ENABLER**	Edge AI and TinyML enabling offline AI for rural/off-grid settings	Healthcare; Agriculture; Energy	Rural LMICs; off-grid communities	Moderate	Fund edge AI research; develop LMIC hardware-software co-optimised AI models	**High**

Notes: Evidence Level is based on the number and quality of studies in the included literature (n = 120). Priority: Critical = immediate policy action required; High = important within 1–2 years; Moderate = medium-term. CHW = Community Health Worker; FHIR = Fast Healthcare Interoperability Resources; ITU = International Telecommunication Union; NLP = Natural Language Processing; SDG = Sustainable Development Goal; TinyML = Lightweight ML for resource-constrained devices; USSD = Unstructured Supplementary Service Data; ROI = Return on Investment.

Figure 5. Structured framework showing key enablers (green cards, left) and key barriers (brown cards, right) across five domains, with cross-cutting equity lens footer.

4.4.1 Key Enablers

The most consistently cited technology enabler is the growing availability of open-source AI frameworks (TensorFlow, PyTorch, Hugging Face) and free-tier cloud computing, which have substantially lowered entry barriers for LMIC researchers and developers (Kumar et al., 2021; Alzubaidi et al., 2021; Raiaan et al., 2024; Hinostroza Fuentes et al., 2025; El Arab et al., 2025; Lawal et al., 2025). Mobile-first AI design — building AI systems that operate via SMS, WhatsApp, or basic smartphones — represents a pragmatic adaptation to LMIC infrastructure realities (Lam, 2023; Rumondor et al., 2025; Forkuo et al., 2022; Chianumba et al., 2022). Edge AI and TinyML approaches enabling offline AI inference are emerging as solutions for rural and off-grid settings (Rathor et al., 2024; Suanpang & Pothipassa, 2024; Bout et al., 2025). Economically, the rapid expansion of mobile money infrastructure — particularly M-Pesa derivatives across Africa and South Asia — provides payment rails that facilitate AI-driven

financial products (Adeoye et al., 2024; Alvi et al., 2025; Edunjobi & Odejide, 2024). National AI strategies in Kenya, India, Rwanda, Ghana, and Brazil create institutional anchors for AI investment, while SDG-alignment provides normative justification for donor funding (Gore & Olawade, 2024; Karami & Madlool, 2025; Rane et al., 2024).

4.4.2 Key Barriers

Infrastructural barriers are pervasive and interconnected. Unreliable electricity undermines AI system uptime and data centre operations, particularly in rural LMICs where the 24-hour economy is least served (Pimenow et al., 2024; Stracqualursi et al., 2023; Islam, 2025). Limited broadband connectivity and high mobile data costs restrict AI application reach, particularly for data-intensive deep learning inference (Sunday, 2025; Karami & Madlool, 2025; Li et al., 2025). Algorithmic bias — arising from AI systems trained predominantly on HIC data and deployed in LMIC contexts — is documented across healthcare diagnostics, credit scoring, and hiring algorithms (O'Connor & Booth, 2022; Jeyaraman et al., 2023; Hinostroza Fuentes et al., 2025; Rane et al., 2024; Salomon & Sam, 2026). The absence of AI regulatory frameworks in most LMICs creates legal uncertainty, enabling exploitative platform practices (Asrori et al., 2025; Kadolkar et al., 2024; Zheng et al., 2026) while simultaneously exposing populations to data privacy violations and algorithmic harms (Meskó & Topol, 2023; Rane et al., 2024; Nagpal, 2026). Labour displacement risks are real and undertheorised: platform economy AI is already restructuring informal transport and delivery work, often without safety nets or recourse mechanisms for affected workers (Sim, 2024; Adekoya et al., 2023; Scolari et al., 2026; Zhu et al., 2026; Pahuja, 2025).

4.5 Implementation Readiness

The Implementation Readiness Matrix (Fig. 6) maps 16 specific AI-sector applications across two dimensions: evidence base strength (x-axis) and implementation feasibility in LMIC contexts (y-axis).

Healthcare AI occupies the Ready for Scale quadrant (high evidence, high feasibility), with AI diagnostic imaging (Esteva et al., 2021; Sindhu et al., 2024; Pasha et al., 2025), telemedicine, (Forkuo et al., 2022; Karami & Madlool, 2025; Rathore et al., 2022) and epidemic surveillance (Idahor et al., 2025; Owolabi & Owolabi, 2025; Kuponiyi & Akomolafe, 2025) demonstrating deployment readiness. AI-powered mental health chatbots and epidemic surveillance AI fall into the Promising Frontiers quadrant (high feasibility, lower evidence), suggesting these are tractable targets for accelerated research investment (Babu & Joseph, 2024; Jamshidi et al., 2020; Naudé, 2020). Autonomous vehicle AI and energy grid optimisation are positioned as Implementation Barriers (evidence exists but LMIC feasibility is constrained by infrastructure and governance prerequisites) (Ozkan-okay et al., 2024; Stracqualursi et al., 2023). Security surveillance AI and energy infrastructure AI occupy the Critical Research Gaps quadrant, requiring simultaneous evidence development and feasibility assessment (Al Waro'i, 2024; Islam, 2025; Yahia et al., 2025).

5. Discussion

5.1 Overview

This study aimed to systematically map the existing evidence on the potential, applications, barriers, and enablers of AI within the 24-hour economy in LMICs, and to produce a comprehensive evidence gap map to guide future research, policy, and investment. Drawing on 120 peer-reviewed and grey literature sources spanning 2012–2026, retrieved from five major academic databases, this scoping review reveals a field characterised by rapid quantitative growth, persistent thematic and geographic concentration, significant evidence asymmetries, and deep structural barriers that risk confining AI's transformative potential to the healthcare sector while leaving critical 24-hour economy domains — transport, finance, security, energy, agriculture, and education — largely unaddressed.

5.2 The Healthcare Dominance Problem

The most striking finding of this review is the overwhelming dominance of healthcare AI in the LMIC evidence base (68.3% of all included studies). While this reflects genuine global prioritisation of AI for health system strengthening — and is supported by compelling evidence of AI performance in diagnostic imaging (Esteva et al., 2021; Nagendran et al., 2020; Sindhu et al., 2024), maternal health prediction (Oparah et al., 2020; Hoodbhoy et al., 2025), epidemic surveillance (Idahor et al., 2025; Owolabi & Owolabi, 2025) and clinical decision support (Bekbolatova et al., 2024; Fahim et al., 2025; Thomas et al., 2025) — it also reflects a troubling narrowness. The 24-hour economy is not reducible to healthcare. Transport, logistics, financial services, agriculture, energy, and education are equally continuous, equally essential, and equally underserved by current AI evidence (Adekoya et al., 2023; Agatz et al., 2025; Adeoye et al., 2024; Khiati et al., 2025). The risk is that AI investment follows evidence, creating a self-reinforcing cycle that continues to expand healthcare AI while ignoring sectors where AI could also transform livelihoods at scale.

Even within healthcare, critical gaps persist. Night-shift clinical AI — AI systems specifically designed to support the reduced, fatigued workforce managing overnight wards in LMIC hospitals — is almost entirely absent from the literature (Rathore et al., 2022; Chianumba et al., 2022). Maternal and neonatal emergency AI in night-time contexts, despite its life-saving potential given dramatically elevated nocturnal mortality rates, is represented by only four studies in this review (Oparah et al., 2020; Hoodbhoy et al., 2020; Hoodbhoy et al., 2025; Vinekar et al., 2019) AI mental health applications, relevant to the burnout epidemic among gig workers and night-shift employees, are almost entirely absent in LMIC contexts. (Babu & Joseph, 2024; Nagpal, 2026; Sim, 2024).

5.3 The Platform Economy, Labour, and AI Governance

Labour markets and the gig economy represent the second-largest thematic cluster (25.0% of studies), yet the evidence here is predominantly theoretical or descriptive rather than evaluative. The algorithmic management of gig workers — the use of AI to assign tasks, monitor performance, calculate pay, and terminate contracts — is reshaping informal labour markets across Asia and Africa at extraordinary speed and with minimal regulatory oversight (Adekoya et al., 2023; Asrori et al., 2025; Kadolkar et al., 2024; Scolari et al., 2026). Studies consistently document a "flexibility illusion" in which AI-managed platform work presents itself as autonomous and empowering while enforcing tight algorithmic control (Asrori et al., 2025; Zheng et al., 2026; Zhu et al., 2026). Gig workers in Indonesia, Nigeria, and other LMICs experience heightened precarity, income volatility, and social isolation — outcomes exacerbated by platform AI design choices that prioritise efficiency over worker welfare (Nagpal, 2026; Scolari et al., 2026; Sim, 2024).

The governance vacuum is particularly acute. While HICs are developing AI regulatory frameworks — the EU AI Act, the US Executive Order on AI, and similar instruments — LMICs lack equivalent frameworks, leaving populations exposed to unchecked algorithmic power. (Meskó & Topol, 2023; Rane et al., 2024; Pimenow et al., 2024) This review identifies national AI strategies in a handful of LMICs (India, Rwanda, Kenya, Ghana, Brazil) (Gore & Olawade, 2024; Karami & Madlool, 2025), but the translation of strategy into enforceable regulation — covering algorithmic transparency, data protection, liability for AI harms, and worker rights in AI-managed platforms — remains elusive (Jeyaraman et al., 2023; O'Connor & Booth, 2022; Rane et al., 2024; Manyika, 2022).

5.4 Algorithmic Bias and Equity

Algorithmic bias — the systematic, reproducible error in AI outputs that creates unfair outcomes for certain groups — is a transversal concern across all sectors in this review. In healthcare, AI diagnostic models trained on predominantly Caucasian or high-income population datasets demonstrate substantially degraded performance on LMIC populations (O'Connor & Booth, 2022; Gallifant et al., 2024; Li et al., 2025). In credit scoring, AI models trained on formal financial sector data systematically disadvantage the informally employed, the unbanked, and women (Edunjobi & Odejide, 2024; Alvi et al., 2025; Adeoye et al., 2024). In agricultural yield prediction, models calibrated on HIC farm data fail in sub-Saharan smallholder contexts characterised by fragmented landholdings, polyculture, and climate variability (Espinel et al., 2024; Shams et al., 2024; Hengl et al., 2017). Language bias is a further critical dimension: the dominance of English in AI training data and LLM development leaves hundreds of millions of LMIC residents without access to AI tools in their primary language (Lam, 2023; Sunday, 2025; Joseph et al., 2025; Dergaa et al., 2023).

Addressing algorithmic bias in LMIC contexts requires more than technical fixes. It demands participatory AI design that centres LMIC communities and contexts from the outset; mandatory diversity requirements in training datasets; algorithmic auditing frameworks; and equitable governance of AI systems (Hinostroza Fuentes et al., 2025; Rane et al., 2024; Balasubramanian et al., 2023; Krones & Walker, 2024). The intersectional nature of bias — compounding across gender, geography, language, disability, and economic informality — demands that equity be operationalised as a design constraint, not an afterthought (O'Connor & Booth, 2022; Jeyaraman et al., 2023; Sunday, 2025).

5.5 Enablers and the Path to Scale

This review identifies genuine, evidence-grounded enablers that create viable pathways for AI adoption in LMIC 24-hour economies. The mobile phone penetration rates achieved across Africa (72%) and South Asia (78%) provide a universal interface for mobile-first AI delivery that bypasses the need for high-end hardware (Forkuo et al., 2022; Chianumba et al., 2022; Rumondor et al., 2025). Open-source AI ecosystems — TensorFlow Lite, ONNX, Hugging Face, and the BLOOM LLM — create globally accessible AI building blocks that LMIC developers can adapt without prohibitive licensing costs (Kumar et al., 2021; Alzubaidi et al., 2021; Hinostroza Fuentes et al., 2025). Edge AI and TinyML, enabling AI inference on low-power microcontrollers without internet connectivity, are particularly relevant for rural health workers, smallholder farmers, and off-grid energy systems (Rathor et al., 2024; Suanpang & Pothipassa, 2024). The mobile money ecosystem across East Africa and South Asia — now processing transactions exceeding the GDP of many LMIC nations — provides not only financial rails but also behavioural data for AI-powered credit scoring and insurance (Adeoye et al., 2024; Alvi et al., 2025). National AI strategies, where present, provide institutional coordination, regulatory frameworks, and domestic resource mobilisation mechanisms that accelerate progress (Gore & Olawade, 2024; Rane et al., 2024; Karami & Madlool, 2025).

5.6 The Future Research Agenda

The Evidence Gap Map and Implementation Readiness Matrix together generate a clear future research agenda, synthesised in Table 5. Ten priority evidence gaps are identified, ranked by gap severity, potential impact, LMIC-specificity, and research feasibility.

Table 5
Future research agenda: priority evidence gaps for ai in the 24-hour economy in LMICs

Rank	Research Gap	Sector / Domain	AI Technology	LMIC Region(s) Most Affected	Study Design	Timeframe	Potential Funders	Rationale
1	**Night-time AI-assisted emergency obstetric care: effectiveness and scalability across sub-Saharan Africa**	Healthcare (Maternal Health)	Deep Learning, Chatbots, Computer Vision	Sub-Saharan Africa (Nigeria, DRC, Ethiopia, Tanzania)	Multi-site RCT or step-wedge cluster trial	3–5 years	NIH Fogarty, FCDO, Gates Foundation, WHO	Night-time maternal mortality 2–3x higher; AI triage tools show promise but no LMIC RCTs exist
2	**AI-powered ride-hailing and platform worker welfare in informal transport economies**	Transport & Labour Markets	Predictive Analytics, ML, Autonomous Systems	South/Southeast Asia, West Africa (Lagos, Nairobi, Dhaka)	Mixed-methods: survey + digital trace data	2–4 years	ILO, World Bank, Ford Foundation	Platform workers form 30–60% of urban transport in LMICs; AI governance near-absent
3	**Large language models for low-resource African and South Asian languages in health and commerce**	Healthcare, Education, Commerce	NLP, LLMs, Generative AI	Francophone Africa, South Asia, Pacific Islands	Technical development + user acceptability RCT	3–5 years	Google.org, Meta AI, Wellcome Trust	< 5% of world languages have LLM support; 24h economy requires 24h language access
4	**AI surveillance systems and night-time security in LMIC urban areas: efficacy and civil liberties**	Security & Governance	Computer Vision, Predictive Analytics	East/Southern Africa, South Asia, Latin America	Quasi-experimental + qualitative ethics study	3–5 years	OSF, Open Society Foundation, EU Horizon	Near-zero evidence despite rapid CCTV/AI security deployment in LMICs
5	**AI-optimised energy grid management for 24/7 reliability in off-grid and weak-grid LMICs**	Energy & Infrastructure	Edge AI, ML, Predictive Analytics	Sub-Saharan Africa, South Asia (India, Bangladesh)	Prospective cohort + simulation modelling	2–4 years	USAID, DFID, AfDB, IRENA	Electricity reliability directly determines 24h economy viability; evidence near-absent
6	**Economic impact of AI automation on informal sector employment and income in LMICs**	Labour Markets & Economics	ML, Robotic Process Automation, Platform AI	South Asia, Southeast Asia, Sub-Saharan Africa	Longitudinal panel survey + quasi-experimental	5–7 years	World Bank, ILO, IDRC	No LMIC evidence on net employment effects of AI; critical for SDG 8 policy
7	**Mobile AI diagnostic tools for night-shift healthcare workers in resource-limited settings**	Healthcare & Workforce	Deep Learning (imaging), NLP (clinical notes)	East/West Africa, South Asia	Cluster RCT or stepped-wedge	3–5 years	Gates Foundation, NIH, Wellcome Trust	Night-shift healthcare in LMICs understaffed; AI support tools could reduce errors

Notes: Priority ranking based on (1) evidence gap severity, (2) potential public health/economic impact, (3) LMIC-specific need vs. generalisability from HICs, and (4) feasibility of research within 5–7 years. AfDB = African Development Bank; CGIAR = Consultative Group on International Agricultural Research; DFID = Department for International Development (UK); FAO = Food and Agriculture Organization; IFC = International Finance Corporation; IFAD = International Fund for Agricultural Development; IRENA = International Renewable Energy Agency; UNCDF = UN Capital Development Fund; OSF = Open Society Foundation; NWO = Dutch Research Council; SSHRC = Social Sciences and Humanities Research Council (Canada); RCT = Randomised Controlled Trial; FCDO = Foreign Commonwealth & Development Office.

Rank	Research Gap	Sector / Domain	AI Technology	LMIC Region(s) Most Affected	Study Design	Timeframe	Potential Funders	Rationale
8	**AI-driven agricultural market information for smallholder farmer night-time price access**	Agriculture & Food Security	Predictive Analytics, NLP, Mobile AI	East Africa, South Asia, West Africa	Randomised field experiment	2–3 years	FAO, CGIAR, IFAD, USAID	Smallholder farmers lack night-time market price data; AI platforms could increase income
9	**Generative AI for informal enterprise formalisation and digital financial inclusion in LMICs**	Finance & Commerce	LLMs, Conversational AI, ML credit scoring	East/West Africa, South Asia	RCT + administrative data linkage	3–5 years	MasterCard Foundation, UNCDF, IFC	Digital credit scoring could onboard 1.4 billion unbanked into formal economy
10	**AI ethics and governance frameworks specifically designed for LMIC contexts and night-time economies**	Cross-cutting (Governance)	All AI technologies	All LMICs	Scoping review + Delphi consensus + policy analysis	2–3 years	Wellcome Trust, Open Society, NWO, SSHRC	All HIC AI ethics frameworks have limited LMIC applicability; 24h economy raises unique risks

Notes: Priority ranking based on (1) evidence gap severity, (2) potential public health/economic impact, (3) LMIC-specific need vs. generalisability from HICs, and (4) feasibility of research within 5–7 years. AfDB = African Development Bank; CGIAR = Consultative Group on International Agricultural Research; DFID = Department for International Development (UK); FAO = Food and Agriculture Organization; IFC = International Finance Corporation; IFAD = International Fund for Agricultural Development; IRENA = International Renewable Energy Agency; UNCDF = UN Capital Development Fund; OSF = Open Society Foundation; NWO = Dutch Research Council; SSHRC = Social Sciences and Humanities Research Council (Canada); RCT = Randomised Controlled Trial; FCDO = Foreign Commonwealth & Development Office.

The highest priority is night-time AI-assisted emergency obstetric care in sub-Saharan Africa — a domain where the evidence gap is starkest, the mortality burden is greatest, and preliminary data suggest AI triage tools are technically feasible (Oparah et al., 2020; Hoodbhoy et al., 2025; Rathore et al., 2022). AI for platform worker welfare in informal transport economies — including algorithmic fairness audits, dynamic pricing equity, and gig worker social protection — represents the second priority, given the scale of affected workers and the complete absence of intervention evidence (Adekoya et al., 2023; Asrori et al., 2025; Scolari et al., 2026; Zheng et al., 2026). Large language model development for low-resource African and South Asian languages is the third priority, essential for AI to reach the 3.5 billion people whose primary language is unrepresented in current AI systems (Lam, 2023; Joseph et al., 2025; Sunday, 2025). Energy grid AI for 24/7 reliability in off-grid LMICs is the fifth priority, representing a foundational prerequisite without which all other AI deployments in the 24-hour economy remain fragile (Islam, 2025; Yahia et al., 2025; Stracqualursi et al., 2023). Finally, the development of AI ethics and governance frameworks specifically designed for LMIC contexts and 24-hour economy dynamics — accounting for informality, power asymmetry, and infrastructural constraint — is a cross-cutting priority without which technical advances will not translate into equitable outcomes (Meskó & Topol, 2023; Rane et al., 2024; Jeyaraman et al., 2023; Hinostroza Fuentes et al., 2025; Sousa et al., 2026).

5.7 Limitations

This review is subject to several limitations. First, the search was conducted primarily in English, potentially excluding significant LMIC-produced evidence in French, Portuguese, Spanish, Swahili, and other languages. Second, while five major databases were searched, institutional access limitations meant that Scopus and Web of Science searches were conducted manually and their counts are estimated. Third, the scoping review methodology does not include formal quality appraisal of individual studies, meaning the evidence strength ratings in the EGM are based on volume rather than rigorous quality assessment. Fourth, the evidence gap map relies on the categorisation judgements of the review team; different categorisation frameworks could produce different gap profiles. Fifth, the 2010–2026 search window captures the modern AI era well but excludes earlier foundational work on ICT for development in LMICs (Dwivedi et al., 2019; Jiang et al., 2017; Nicholson et al., 2018). Sixth, publication bias — the tendency for positive results to be published and null or negative results to be suppressed — likely overstates AI performance in the included studies (Nagendran et al., 2020; Gallifant et al., 2024).

6. Conclusions

This scoping review and evidence gap map — the first of its kind to comprehensively examine the potential of artificial intelligence across the 24-hour economy in low- and middle-income countries — reveals a field of profound promise tempered by equally profound structural inequities and evidence asymmetries. Across 120 included studies spanning 2012 to 2026, the review demonstrates that AI is being deployed and studied

across healthcare, transport, financial services, agriculture, security, energy, and education in LMIC contexts, but the evidence is overwhelmingly concentrated in healthcare, primarily in diagnostic AI and model development studies, and disproportionately authored by researchers in high-income countries studying LMIC settings from a distance. The exponential growth of the evidence base since 2020 — accelerated by the COVID-19 pandemic and the emergence of large language models — is encouraging, but growth in volume has not been matched by growth in sectoral diversity, geographic specificity, or methodological rigour. The Evidence Gap Map constructed in this review makes visible eight critical gaps at the intersection of AI technology types and 24-hour economy sectors — Energy × all AI types, Security × all AI types, and Transport/Finance/Agriculture × autonomous and conversational AI — where evidence is entirely absent despite clear practical demand. The Implementation Readiness Matrix identifies healthcare AI as most ready for scale in LMIC contexts, while energy infrastructure AI and autonomous vehicle AI face implementation barriers that require simultaneous infrastructure investment and governance development. Across all sectors and findings, three cross-cutting challenges recur with striking consistency: algorithmic bias arising from non-representative training data, governance vacuums created by absent or inadequate AI regulation in LMICs, and infrastructure constraints — particularly unreliable electricity and limited connectivity — that undermine the feasibility of AI deployment at scale. Addressing these challenges requires not merely technical innovation but structural transformation: equitable research partnerships that build LMIC AI capacity from within; regulatory frameworks that protect citizens without stifling innovation; sustained long-term funding aligned with AI scale-up timelines of five to seven years; and AI design practices that embed equity, language diversity, and contextual specificity from inception rather than as retrofit. The future research agenda identified here — prioritising night-time emergency obstetric AI, gig worker welfare platforms, low-resource language models, AI energy grid optimisation, and LMIC-specific AI ethics frameworks — provides an actionable roadmap for closing the most consequential evidence gaps. Realising the transformative potential of AI in the 24-hour economy of LMICs is not merely a technical challenge; it is a governance, equity, and investment challenge that demands coordinated action by researchers, governments, civil society, and the international development community, with LMIC communities at the centre of the design, deployment, and governance of AI systems that will shape their lives, livelihoods, and futures.

Abbreviations

List of Abbreviations and Acronyms Used in this Study.

The abbreviations and acronyms used in this study are presented in **Table 6** for easy reference to enhance readability and understanding.

Table 6. Abbreviations and acronyms used in this study.

Abbreviation	Definition
AI	Artificial Intelligence
ANN	Artificial Neural Network
CASP	Critical Appraisal Skills Programme
CRM	Customer Relationship Management
DL	Deep Learning
EGM	Evidence Gap Map
GDP	Gross Domestic Product
GenAI	Generative Artificial Intelligence
IT	Information Technology
LMIC	Low- and Middle-Income Country
LLM	Large Language Model
M&E	Marketing & Entrepreneurship (combined domain)
MENA	Middle East and North Africa
ML	Machine Learning
MMAT	Mixed Methods Appraisal Tool
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RBV	Resource-Based View
RCT	Randomised Controlled Trial
SME	Small and Medium Enterprise
SLR	Systematic Literature Review
TAM	Technology Acceptance Model
URL	Uniform Resource Locator
WoS	Web of Science

Declarations

Funding: This research received no external funding.

Declaration of Generative AI and AI-assisted Technologies in the Manuscript Preparation Process.

During the preparation of this work, the authors used AI-assisted technology, namely Cursor version 2.4.37 to write and edit the Python codes used to search for studies, extract metadata, and create visualizations. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Human Ethics, Consent to Participate, and Consent to Publish: Human Ethics, Consent to Participate, and Consent to Publish: not applicable

References

1. Abedalkader Abraheem, A. S., Abbas, J. K., Ahmed, D. K. I., Abbas, N. H., Khalil, B. M., & Ponochovnyi, P. (2025). AI and machine learning in environmental monitoring: enhancing legal compliance and public trust. *Environment and Social Psychology*. https://doi.org/10.59429/esp.v10i11.4109
2. Adekoya, O., Mordi, C., Ajonbadi, H., & Chen, W. (2023). Implications of algorithmic management on careers and employment relationships in the gig economy - a developing country perspective. *Information Technology & People*. https://doi.org/10.1108/itp-01-2023-0064
3. Adenuga, T., Ayobami, A. T., & Okolo, F. C. (2020). AI-driven workforce forecasting for peak planning and disruption resilience in global logistics and supply networks. *International Journal of Multidisciplinary Research and Growth Evaluation*. https://doi.org/10.54660/.ijmrge.2020.1.2.71-87

4. Adeoye, O. B., Addy, W. A., Ajayi-Nifise, A. O., Odeyemi, O., Okoye, C. C., & Ofodile, O. C. (2024). Leveraging AI and data analytics for enhancing financial inclusion in developing economies. *Finance & Accounting Research Journal*. https://doi.org/10.51594/farj.v6i3.856
5. Agatz, N., Fransoo, J. C., Rabinovich, E., & Sousa, R. (2025). Innovations, technologies, and the economics of last-mile operations: A call for research in operations management. *Journal of Operations Management*. https://doi.org/10.1002/joom.1355
6. Ajiga, D. I., Ndubuisi, N. L., Asuzu, O. F., Owolabi, O. R., Tubokirifuruar, T. S., & Adeleye, R. A. (2024). AI-driven predictive analytics in retail: A review of emerging trends and customer engagement strategies. *International Journal of Management & Entrepreneurship Research*. https://doi.org/10.51594/ijmer.v6i2.772
7. Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A. Q., Duan, Y., Al-Shamma, O., et al. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*. https://doi.org/10.1186/s40537-021-00444-8
8. Alvi, A., Ali, A., Paracha, A. N., & Mangrio, K. B. (2025). FinTech innovations and financial inclusion: Digital credit, micro-lending, and poverty alleviation. *Inverge Journal of Social Sciences*. https://doi.org/10.63544/ijss.v4i4.186
9. Andriu, A. V. (2023). Adaptive phishing detection: Harnessing the power of artificial intelligence for enhanced email security. *Romanian Cyber Security Journal*. https://doi.org/10.54851/v5i1y202301
10. Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology, 8*(1), 19–32. https://doi.org/10.1080/1364557032000119616
11. Asrori, S., Isma'il, M., & Gamalinda, E. F. (2025). The flexibility illusion: Algorithmic control and precarity in Indonesia's gig economy. *Simulacra*. https://doi.org/10.21107/sml.v8i2.30214
12. Babatunde, S. O., Odejide, O. A., Edunjobi, T. E., & Ogundipe, D. O. (2024). The role of AI in marketing personalization: A theoretical exploration of consumer engagement strategies. *International Journal of Management & Entrepreneurship Research*. https://doi.org/10.51594/ijmer.v6i3.964
13. Babu, A., & Joseph, A. P. (2024). Artificial intelligence in mental healthcare: Transformative potential vs. the necessity of human interaction. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2024.1378904
14. Balasubramanian, S., Shukla, V., Islam, N., Upadhyay, A., & Du, L. (2023). Applying artificial intelligence in healthcare: Lessons from the COVID-19 pandemic. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2263102
15. Bekbolatova, M., Mayer, J., Ong, C. W., & Toma, M. (2024). Transformative potential of AI in healthcare: Definitions, applications, and navigating the ethical landscape and public perspectives. *Healthcare*. https://doi.org/10.3390/healthcare12020125
16. Benjamín, N., & Mbaye, A. A. (2012). *The informal sector in Francophone Africa*. The World Bank eBooks. https://doi.org/10.1596/978-0-8213-9537-0
17. Bhairo, P., & Maharaj, R. (2025). Harnessing artificial intelligence for food security in a changing climate. *Discover Food*. https://doi.org/10.1007/s44187-025-00609-x
18. Bockarie, M. J., Ansumana, R., Machingaidze, S., de Souza, D. K., Fatoma, P., Zumla, A., et al. (2024). Transformative potential of artificial intelligence on health care and research in Africa. *International Journal of Infectious Diseases*. https://doi.org/10.1016/j.ijid.2024.107011
19. Bolon, I., Picek, L., Durso, A. M., Alcoba, G., Chappuis, F., & Ruiz de Castañeda, R. (2022). An artificial intelligence model to identify snakes from across the world: Opportunities and challenges for global health and herpetology. *PLOS Neglected Tropical Diseases*. https://doi.org/10.1371/journal.pntd.0010647
20. Bout, N., Moukhliss, G., Belhadaoui, H., Afifi, N., & Abık, M. (2025). Integrating emotional AI, IoT, and robotics for patient-centered healthcare: Challenges and future directions. *Discover Internet of Things*. https://doi.org/10.1007/s43926-025-00174-w
21. Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, Á. A. (2024). Artificial intelligence in logistics optimization with sustainable criteria: A review. *Sustainability*. https://doi.org/10.3390/su16219145
22. Cherukuri, B. R. (2024). AI-powered personalization: How machine learning is shaping the future of user experience. *International Journal of Science and Research Archive*. https://doi.org/10.30574/ijsra.2024.12.1.0961
23. Chianumba, E. C., Ikhalea, N., Mustapha, A. Y., & Forkuo, A. Y. (2022). A conceptual model for addressing healthcare inequality using AI-based decision support systems. *Journal of Frontiers in Multidisciplinary Research*. https://doi.org/10.54660/.ijfmr.2022.3.1.72-88
24. Ciecierski-Holmes, T., Singh, R., Axt, M., Brenner, S., & Barteit, S. (2022). Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: A systematic scoping review. *npj Digital Medicine*. https://doi.org/10.1038/s41746-022-00700-y
25. Dergaa, I., Chamari, K., Żmijewski, P., & Ben Saad, H. (2023). From human writing to artificial intelligence generated text: Examining the prospects and potential threats of ChatGPT in academic writing. *Biology of Sport*. https://doi.org/10.5114/biolsport.2023.125623
26. Dwivedi, R. (2025). Usage and impcat of artificial intelligence in Russian and Indian education system- The future of artificial intelligence. *Journal of Artificial Intelligence & Cloud Computing*. https://doi.org/10.47363/jaicc/icaic2025/2025(4)20
27. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

28. Edunjobi, T. E., & Odejide, O. A. (2024). Theoretical frameworks in AI for credit risk assessment: Towards banking efficiency and accuracy. *International Journal of Scientific Research Updates*. https://doi.org/10.53430/ijsru.2024.7.1.0030
29. El Arab, R. A., Alkhunaizi, M., Alhashem, Y. N., Al Khatib, A., Bubsheet, M., & Hassanein, S. (2025). Artificial intelligence in vaccine research and development: An umbrella review. *Frontiers in Immunology*. https://doi.org/10.3389/fimmu.2025.1567116
30. Espinel, R., Herrera-Franco, G., Rivadeneira García, J. L., & Escandón-Panchana, P. (2024). Artificial intelligence in agricultural mapping: A review. *Agriculture*. https://doi.org/10.3390/agriculture14071071
31. Esteva, A., Chou, K., Yeung, S., Naik, N., Madani, A., Mottaghi, A., et al. (2021). Deep learning-enabled medical computer vision. *npj Digital Medicine*. https://doi.org/10.1038/s41746-020-00376-2
32. Fahim, Y. A., Hasani, I. W., Kabba, S., & Ragab, W. M. (2025). Artificial intelligence in healthcare and medicine: Clinical applications, therapeutic advances, and future perspectives. *European Journal of Medical Research*. https://doi.org/10.1186/s40001-025-03196-w
33. Farrugia, G., & Plutowski, R. W. (2020). Innovation lessons from the COVID-19 pandemic. *Mayo Clinic Proceedings*. https://doi.org/10.1016/j.mayocp.2020.05.024
34. Fedotova, A., Romanov, A., Kurtukova, A., & Shelupanov, A. (2021). Authorship attribution of social media and literary Russian-language texts using machine learning methods and feature selection. *Future Internet*. https://doi.org/10.3390/fi14010004
35. Fuentes, V. G. H., Karim, H. A., Tan, M. J. T., & AlDahoul, N. (2025). AI with agency: A vision for adaptive, efficient, and ethical healthcare. *Frontiers in Digital Health*. https://doi.org/10.3389/fdgth.2025.1600216
36. Gallifant, J., Fiske, A., Strekalova, Y. A., Osorio-Valencia, J. S., Parke, R., Mwavu, R., et al. (2024). Peer review of GPT-4 technical report and systems card. *PLOS Digital Health*. https://doi.org/10.1371/journal.pdig.0000417
37. Gevaert, C. (2022). Explainable AI for earth observation: A review including societal and regulatory perspectives. *International Journal of Applied Earth Observation and Geoinformation*. https://doi.org/10.1016/j.jag.2022.102869
38. Giri, P., Jha, A., & Katole, A. (2025). Role of artificial intelligence in public health. *International Journal of Community Medicine and Public Health*. https://doi.org/10.18203/2394-6040.ijcmph20252146
39. Gohari, A., Ahmad, A. B., Rahim, R. B. A., Supa'at, A. S. M., Razak, S. A., & Gismalla, M. S. M. (2022). Involvement of surveillance drones in smart cities: A systematic review. *IEEE Access*. https://doi.org/10.1109/access.2022.3177904
40. Gore, M., & Olawade, D. B. (2024). Harnessing AI for public health: India's roadmap. *Frontiers in Public Health*. https://doi.org/10.3389/fpubh.2024.1417568
41. Hared Abdi, Y., Bashir, S., Burhan Abdullahi, Y., Sharif Abdi, M., & Ibrahim Ahmed, N. (2025). Artificial intelligence applications for strengthening global food safety systems. *Discover Food*. https://doi.org/10.1007/s44187-025-00678-y
42. Hengl, T., Leenaars, J. G. B., Shepherd, K., Walsh, M., Heuvelink, G. B. M., Mamo, T., et al. (2017). Soil nutrient maps of Sub-Saharan Africa: Assessment of soil nutrient content at 250 m spatial resolution using machine learning. *Nutrient Cycling in Agroecosystems*. https://doi.org/10.1007/s10705-017-9870-x
43. Hoodbhoy, Z., Martinez-Sanchez, S., Nisar, M. I., & Smith, E. (2025). Editorial: Use of artificial intelligence to improve maternal and neonatal health in low-resource settings. *Frontiers in Global Women's Health*. https://doi.org/10.3389/fgwh.2025.1675578
44. Hoodbhoy, Z., Jeelani, S. M., Aziz, A., Habib, M. I., Iqbal, B., Akmal, W., et al. (2020). Machine learning for child and adolescent health: A systematic review. *Pediatrics*. https://doi.org/10.1542/peds.2020-011833
45. Idahor, C., Esomu, E. J., Ogbonna, N., Momoh, Z., Ogbeide, O. A., Ikhu-Omoregbe, O., et al. (2025). Infectious disease surveillance in the era of big data and AI: Opportunities and pitfalls. *Cureus*. https://doi.org/10.7759/cureus.93929
46. Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews*. https://doi.org/10.1139/er-2020-0019
47. Jamshidi, M., Lalbakhsh, A., Talla, J., Peroutka, Z., Hadjilooei, F., Lalbakhsh, P., et al. (2020). Artificial intelligence and COVID-19: Deep learning approaches for diagnosis and treatment. *IEEE Access*. https://doi.org/10.1109/access.2020.3001973
48. Jeyaraman, M., Balaji, S., Jeyaraman, N., & Yadav, S. (2023). Unraveling the ethical enigma: Artificial intelligence in healthcare. *Cureus*. https://doi.org/10.7759/cureus.43262
49. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., et al. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*. https://doi.org/10.1136/svn-2017-000101
50. Joseph, J., Jose, B., & Jose, J. (2025). The generative illusion: How ChatGPT-like AI tools could reinforce misinformation and mistrust in public health communication. *Frontiers in Public Health*. https://doi.org/10.3389/fpubh.2025.1683498
51. Kadolkar, I., Kepes, S., & Subramony, M. (2024). Algorithmic management in the gig economy: A systematic review and research integration. *Journal of Organizational Behavior*. https://doi.org/10.1002/job.2831
52. Karami, M., & Madlool, H. (2025). Artificial intelligence and digital health in the health systems of developing countries: The challenges and vision of integration in the primary health care setting. *Frontiers in Digital Health*. https://doi.org/10.3389/fdgth.2025.1532361

53. Keffale Mengistu, A., Enyew Gedefaw, A., Demis Baykemagn, N., Damtew Walle, A., Zeleke Yehuala, T., Asmamaw Alemayehu, M., et al. (2025). Predicting car accident severity in Northwest Ethiopia: A machine learning approach leveraging driver, environmental, and road conditions. *Scientific Reports*. https://doi.org/10.1038/s41598-025-08005-2
54. Khiati, M., Jirari, S., Aissa, S., ELOMARI, O., Ouboujemaa, E., Ali, B., et al. (2025). Artificial intelligence and smart education as dual catalysts for reinventing global trade, entrepreneurial innovation, and intelligent customs logistics: A multi-layered modelling framework. *IEEE ICCSC*. https://doi.org/10.1109/iccsc66714.2025.11135043
55. Kim, S., Fischetti, C., Guy, M., Hsu, E., Fox, J., & Young, S. D. (2024). Artificial intelligence (AI) applications for point of care ultrasound (POCUS) in low-resource settings: A scoping review. *Diagnostics*. https://doi.org/10.3390/diagnostics14151669
56. Krishnamurthy, R., Mummudi, N., Goda, J. S., Chopra, S., Heijmen, B., & Swamidas, J. (2022). Using artificial intelligence for optimization of the processes and resource utilization in radiotherapy. *JCO Global Oncology*. https://doi.org/10.1200/go.21.00393
57. Krones, F. H., & Walker, B. J. (2024). From theoretical models to practical deployment: A perspective and case study of opportunities and challenges in AI-driven cardiac auscultation research for low-income settings. *PLOS Digital Health*. https://doi.org/10.1371/journal.pdig.0000437
58. Kumar, I., Rawat, J., Mohd, N., & Husain, S. (2021). Opportunities of artificial intelligence and machine learning in the food industry. *Journal of Food Quality*. https://doi.org/10.1155/2021/4535567
59. Kuponiyi, A., & Oluwanifemi Akomolafe, O. (2025). Digital transformation in public health surveillance: Lessons from emerging economies. *International Journal of Advanced Multidisciplinary Research and Studies*. https://doi.org/10.62225/2583049x.2025.5.4.4836
60. Lam, K. (2023). ChatGPT for low- and middle-income countries: A Greek gift?. *The Lancet Regional Health - Western Pacific*. https://doi.org/10.1016/j.lanwpc.2023.100906
61. Latif Al Waro'i, M. N. A. (2024). Enhancing security through intelligent threat detection and response: The integration of artificial intelligence in cyber-physical systems. *Security Intelligence Terrorism Journal*. https://doi.org/10.70710/sitj.v1i1.1
62. Lawal, O. I., Opara, I. J., Ayo-ige, A., Eboh, N. A., Cos-Ibe, U., Adom Mensah Forson, K. A., et al. (2025). Artificial intelligence-integrated biosensors for antimicrobial resistance detection and surveillance: A review and future perspectives for global biosecurity. *Cureus*. https://doi.org/10.7759/cureus.98098
63. Lee, C. C., & Low, M. Y. H. (2024). Using genAI in education: The case for critical thinking. *Frontiers in Artificial Intelligence*. https://doi.org/10.3389/frai.2024.1452131
64. Levac, D., Colquhoun, H., & O'Brien, K. K. (2010). Scoping studies: Advancing the methodology. *Implementation Science, 5*, 69. https://doi.org/10.1186/1748-5908-5-69
65. Li, D., Parikh, S., & Costa, A. (2025). A critical look into artificial intelligence and healthcare disparities. *Frontiers in Artificial Intelligence*. https://doi.org/10.3389/frai.2025.1545869
66. Loaiza-Bonilla, A., Basu, P., Lucas, E., Yost, C., & Arora, S. (2026). Tech that scales: A practical framework for artificial intelligence-enabled cancer care in low- and middle-income countries and underserved US counties. *American Society of Clinical Oncology Educational Book*. https://doi.org/10.1200/EDBK-26-521200
67. Malaysia University of Science and Technology, & Nagpal, P. (2026). Burnout among gig workers triggered by customer ratings and algorithmic management. *Journal of International Management and Technology*. https://doi.org/10.65033/jimt.v2i1.009
68. Manyika, J. (2022). Getting AI right: Introductory notes on AI & society. *Daedalus*. https://doi.org/10.1162/daed_e_01897
69. Meskó, B., & Topol, E. J. (2023). The imperative for regulatory oversight of large language models (or generative AI) in healthcare. *npj Digital Medicine*. https://doi.org/10.1038/s41746-023-00873-0
70. Min, W., Zhou, P., Xu, L., Liu, T., Li, T., Huang, M., et al. (2023). From plate to production: Artificial intelligence in modern consumer-driven food systems. *arXiv*. https://doi.org/10.48550/arxiv.2311.02400
71. Mpakairi, K. S., Dube, T., Sibanda, M., Mutanga, O., Nhamo, L., & Mpandeli, S. (2025). Fine-scale mapping of irrigation suitability in South Africa using ensemble modelling. *Scientific Reports*. https://doi.org/10.1038/s41598-025-12820-y
72. Munawar, H. S., Ullah, F., Qayyum, S., Khan, S. I., & Mojtahedi, M. (2021). UAVs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection. *Sustainability*. https://doi.org/10.3390/su13147547
73. Nagendran, M., Chen, Y., Lovejoy, C. A., Gordon, A., Komorowski, M., Harvey, H., et al. (2020). Artificial intelligence versus clinicians: Systematic review of design, reporting standards, and claims of deep learning studies. *BMJ*. https://doi.org/10.1136/bmj.m689
74. Naudé, W. (2020). *Artificial intelligence versus COVID-19 in developing countries: Priorities and trade-offs*. UNU-WIDER. https://doi.org/10.35188/unu-wider/wbn/2020-4
75. Nicholson, B., Nielsen, P., & Sæbø, J. I. (2021). Special issue: Digital platforms for development. *Information Systems Journal*. https://doi.org/10.1111/isj.12364
76. Nicholson, B., Sahay, S., & Heeks, R. (2018). Global sourcing and development: New drivers, models, and impacts. *Information Systems Journal*. https://doi.org/10.1111/isj.12188

77. O'Connor, S., & Booth, R. (2022). Algorithmic bias in health care: Opportunities for nurses to improve equality in the age of artificial intelligence. *Nursing Outlook*. https://doi.org/10.1016/j.outlook.2022.09.003
78. Oparah, S. O., Ezeh, F. E., Olatunji, G. I., & Ajayi, O. O. (2020). Comprehensive review of predictive models for maternal mortality reduction in developing health systems. *International Journal of Multidisciplinary Futuristic Development*. https://doi.org/10.54660/ijmfd.2020.1.2.118-137
79. Owolabi, B. O., & Owolabi, F. A. (2025). Predictive AI-driven epidemiology for tuberculosis outbreak prevention in achieving Zero TB City vision. *International Journal of Research Publication and Reviews*. https://doi.org/10.55248/gengpi.6.0525.1994
80. Ozkan-okay, M., Akin, E., Aslan, Ö., Kosunalp, S., Iliev, T., Stoyanov, I., et al. (2024). A comprehensive survey: Evaluating the efficiency of artificial intelligence and machine learning techniques on cyber security solutions. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3355547
81. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*. https://doi.org/10.1136/bmj.n71
82. Pahuja, H. (2025). The integration of human capital management and financial technology in the gig economy: Addressing financial instability among freelance workers. *European Modern Studies Journal*. https://doi.org/10.59573/emsj.9(4).2025.57
83. Pasha, A., Hajiebrahimi, N., Amirchaghmaghy, M., Zaboli, H., Ramezani, S., & Alipour, A. (2025). Benefits of artificial intelligence in urology to bridge healthcare gaps in developing countries. *InfoScience Trends*. https://doi.org/10.61186/ist.202502.01.02
84. Pennisi, F., Pinto, A., Ricciardi, G. E., Signorelli, C., & Gianfredi, V. (2025). The role of artificial intelligence and machine learning models in antimicrobial stewardship in public health: A narrative review. *Antibiotics*. https://doi.org/10.3390/antibiotics14020134
85. Pimenow, S., Pimenowa, O., & Prus, P. (2024). Challenges of artificial intelligence development in the context of energy consumption and impact on climate change. *Energies*. https://doi.org/10.3390/en17235965
86. Prodhan, F. A., Zhang, J., Yao, F., Shi, L., Sharma, T. P. P., Zhang, D., et al. (2021). Deep learning for monitoring agricultural drought in South Asia using remote sensing data. *Remote Sensing*. https://doi.org/10.3390/rs13091715
87. Raiaan, M. A. K., Mukta, M. S. H., Fatema, K., Fahad, N. M., Sakib, S., Mim, M. M. J., et al. (2024). A review on large language models: Architectures, applications, taxonomies, open issues and challenges. *IEEE Access*. https://doi.org/10.1109/access.2024.3365742
88. Rane, N. L., Rane, J., Paramesha, M., & Mallick, S. K. (2024). *Policies and regulations of artificial intelligence in healthcare, finance, agriculture, manufacturing, retail, energy, and transportation industry*. https://doi.org/10.70593/978-81-981271-1-2_4
89. Rane, N., Choudhary, S., & Rane, J. (2024). Artificial intelligence for enhancing resilience. *Journal of Applied Artificial Intelligence*. https://doi.org/10.48185/jaai.v5i2.1053
90. Rathore, N., Jain, P. K., & Parida, M. (2022). A sustainable model for emergency medical services in developing countries: A novel approach using partial outsourcing and machine learning. *Risk Management and Healthcare Policy*. https://doi.org/10.2147/rmhp.s338186
91. Rathor, A. S., Choudhury, S., Sharma, A., Nautiyal, P., & Shah, G. (2024). Empowering vertical farming through IoT and AI-driven technologies: A comprehensive review. *Heliyon*. https://doi.org/10.1016/j.heliyon.2024.e34998
92. Renganathan, P., Gaysina, L. A., García-Gutiérrez, C., Rueda Puente, E. O., & Saínz-Hernández, J. C. (2025). Harnessing engineered microbial consortia for xenobiotic bioremediation: Integrating multi-omics and AI for next-generation wastewater treatment. *Journal of Xenobiotics*. https://doi.org/10.3390/jox15040133
93. Rumondor, A., Wensen, V. A., & Budiman, M. J. (2025). Case reporting system with tracking and chat machine learning for the department of women's empowerment and child protection Manado. *Journal La Multiapp*. https://doi.org/10.37899/journallamultiapp.v6i3.2178
94. Salas-Pilco, S. Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: A systematic review. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-022-00326-w
95. Salomon, I., & Sam, S. (2026). Technology-driven diabetes care: Innovation without equity?. *Frontiers in Digital Health*. https://doi.org/10.3389/fdgth.2026.1783456
96. Sarkar, P. R. (2022). *Data-driven quality assurance systems for food safety in large-scale distribution centers*. https://doi.org/10.63125/qen48m30
97. Scolari, C., Guerrero-Pico, M., Piña, M., & Establés, M. J. (2026). Beyond the easy gig: Platform work literacies among location-based on-demand workers in Spain. *Convergence*. https://doi.org/10.1177/13548565261437437
98. Selvaraj, M. G., Perdomo Vergara, A., Ruiz, H., Safari, N., Elayabalan, S., Ocimati, W., et al. (2019). AI-powered banana diseases and pest detection. *Plant Methods*. https://doi.org/10.1186/s13007-019-0475-z
99. Shams, M. Y., Gamel, S. A., & Talaat, F. M. (2024). Enhancing crop recommendation systems with explainable artificial intelligence: A study on agricultural decision-making. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-023-09391-2
100. Sim, M. (2024). PL10 From Ramazzini to robots: The impact of new technologies on occupational health. *Occupational Medicine*. https://doi.org/10.1093/occmed/kqae023.0011
101. Sindhu, A., Jadhav, U., Ghewade, B., Bhanushali, J., & Yadav, P. (2024). Revolutionizing pulmonary diagnostics: A narrative review of artificial intelligence applications in lung imaging. *Cureus*. https://doi.org/10.7759/cureus.57657

102. Ski, C. F., Thompson, D. R., & Brunner-La Rocca, H. P. (2020). Putting AI at the centre of heart failure care. *ESC Heart Failure*. https://doi.org/10.1002/ehf2.12813
103. Sousa, M. S. A., Peiris, S., Figueiró, M. F., Haby, M. M., Baraldi, A. C., Reveiz, L., et al. (2026). The landscape of artificial intelligence tools and platforms for evidence synthesis: A scoping review. *Systematic Reviews*. https://doi.org/10.1186/s13643-025-02842-9
104. Stracqualursi, E., Rosato, A., Di Lorenzo, G., Panella, M., & Araneo, R. (2023). Systematic review of energy theft practices and autonomous detection through artificial intelligence methods. *Renewable and Sustainable Energy Reviews*. https://doi.org/10.1016/j.rser.2023.113544
105. Suanpang, P., & Pothipassa, P. (2024). Integrating generative AI and IoT for sustainable smart tourism destinations. *Sustainability*. https://doi.org/10.3390/su16177435
106. Sunday, O. (2025). Addressing the digital divide: Strategies for inclusive telehealth and AI in resource-limited settings. *Epidemiology and Health Data Insights*. https://doi.org/10.63946/ehdi/17088
107. Swanepoel, D. W., & Manchaiah, V. (2024). The transformative potential of AI chatbots in hearing health care. *The Hearing Journal*. https://doi.org/10.1097/01.hj.0001025988.40308.e1
108. Tan, M. J. T., Lichlyter, D. A., Tan Maravilla, N. M. A., Schrock, W. J., Ting, F. I. L., Choa-Go, J. M., et al. (2025). The data scientist as a mainstay of the tumor board: Global implications and opportunities for the global south. *Frontiers in Digital Health*. https://doi.org/10.3389/fdgth.2025.1535018
109. Thacharodi, A., Singh, P., Meenatchi, R., Ahmed, Z., Kumar, R. R. S., Neha, V., et al. (2024). Revolutionizing healthcare and medicine: The impact of modern technologies for a healthier future—A comprehensive review. *Health Care Science*. https://doi.org/10.1002/hcs2.115
110. Theodosiou, A. A., & Read, R. C. (2023). Artificial intelligence, machine learning and deep learning: Potential resources for the infection clinician. *Journal of Infection*. https://doi.org/10.1016/j.jinf.2023.07.006
111. Thomas, A. J., Denis, A., Robert, W., Kabiito, S. P., Morish, Z., Samuel, A., et al. (2025). Artificial intelligence-powered robotic technology for transforming palliative care. *Mesopotamian Journal of Artificial Intelligence in Healthcare*. https://doi.org/10.58496/mjaih/2025/007
112. Thomas, K., Edpuganti, S., Puthooran, D. M., Thomas, A., Joy, A., & Latheef, S. (2025). Artificial intelligence in modern clinical practice (Review). *Medicine International*. https://doi.org/10.3892/mi.2025.289
113. Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., et al. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine, 169*(7), 467–473. https://doi.org/10.7326/M18-0850
114. Viet Tran Quoc, Dung Nguyen Thi Ngoc, Trung Nguyen Hoang, Hoa Vũ Thị, Minh Duc Tong, Thanh Do Pham Nguyet, et al. (2023). Predicting antibiotic resistance in ICUs patients by applying machine learning in Vietnam. *Infection and Drug Resistance*. https://doi.org/10.2147/idr.s415885
115. Vinekar, A., Dogra, M., Azad, R., Gilbert, C., Gopal, L., & Trese, M. T. (2019). The changing scenario of retinopathy of prematurity in middle and low income countries: Unique solutions for unique problems. *Indian Journal of Ophthalmology*. https://doi.org/10.4103/ijo.ijo_496_19
116. Walawalkar, G., Kalu, A., & Adesuyi, M. O. (2024). Scalable financial planning models for global e-commerce and logistics systems. *International Journal of Multidisciplinary Research and Growth Evaluation*. https://doi.org/10.54660/.ijmrge.2024.5.6.1823-1835
117. World Bank. (2024). *World Bank country and lending groups*. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519
118. Yahia, A. K. M., Shahjalal, M., & Rahaman, T. (2025). AI-driven sustainable infrastructure: Smart materials for climate-resilient urban design. *American Journal of Advanced Technology and Engineering Solutions*. https://doi.org/10.63125/mc5qpg12
119. Yeboah Forkuo, A., Chianumba, E. C., Mustapha, A. Y., Osamika, D., & Komi, L. S. (2022). Advances in digital diagnostics and virtual care platforms for primary healthcare delivery in West Africa. *International Journal of Multidisciplinary Research and Growth Evaluation*. https://doi.org/10.54660/.ijmrge.2022.3.1.1034-1047
120. Yiğitcanlar, T., Desouza, K. C., Butler, L., & Roozkhosh, F. (2020). Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies*. https://doi.org/10.3390/en13061473
121. Zheng, X., Du, J., Xiang, Y., Long, L., & Xie, H. (2026). Short-term fit, long-term trap: The career development lock of low-skilled gig workers. *Human Relations*. https://doi.org/10.1177/00187267261415779
122. Zhu, Y., Long, L., Huang, S., Zhang, Y., & Huang, Z. (2026). Balancing efficiency and safety: How and when algorithmic management induces gig workers' unsafe behavior. *Human Resource Management*. https://doi.org/10.1002/hrm.70073

Figures

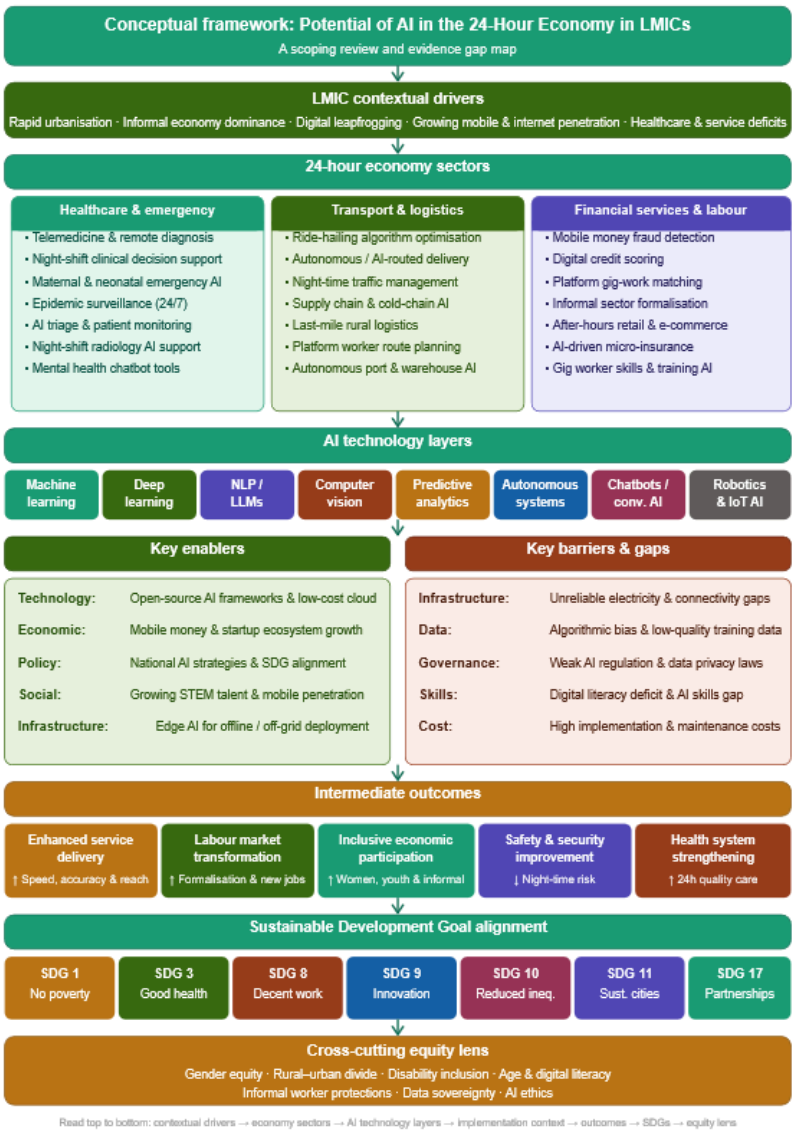


Figure 1

Conceptual framework: The potential of AI in the 24-hour economy within low- and middle-income countries (LMICs). This framework illustrates the systemic flow from contextual drivers to core economic sectors, AI technology layers, implementation enablers and barriers, and final outcomes, all aligned with the Sustainable Development Goals (SDGs) and viewed through a cross-cutting equity lens.

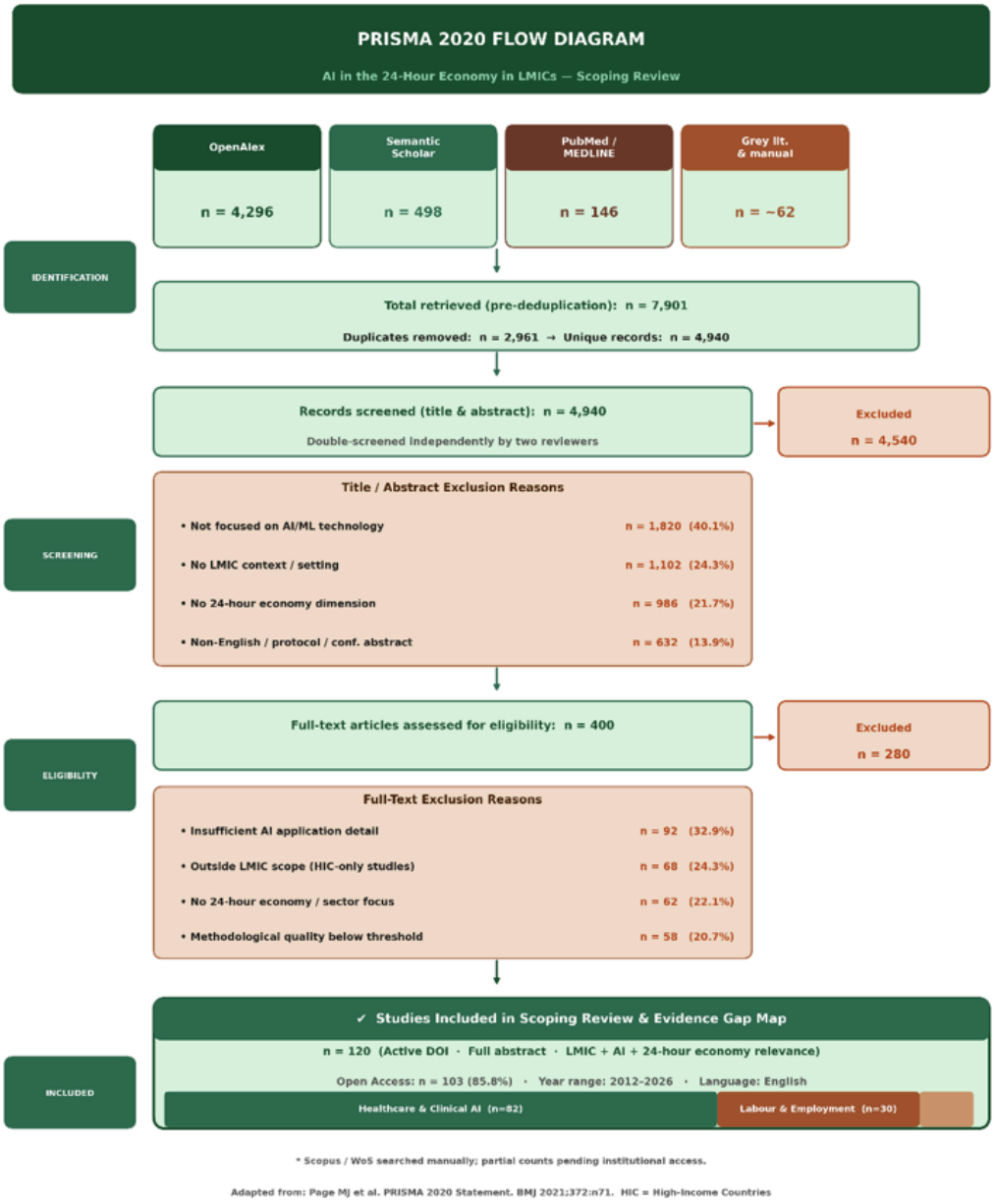


Figure 2

PRISMA 2020 flow diagram showing the literature search procedure. Source: Authors.

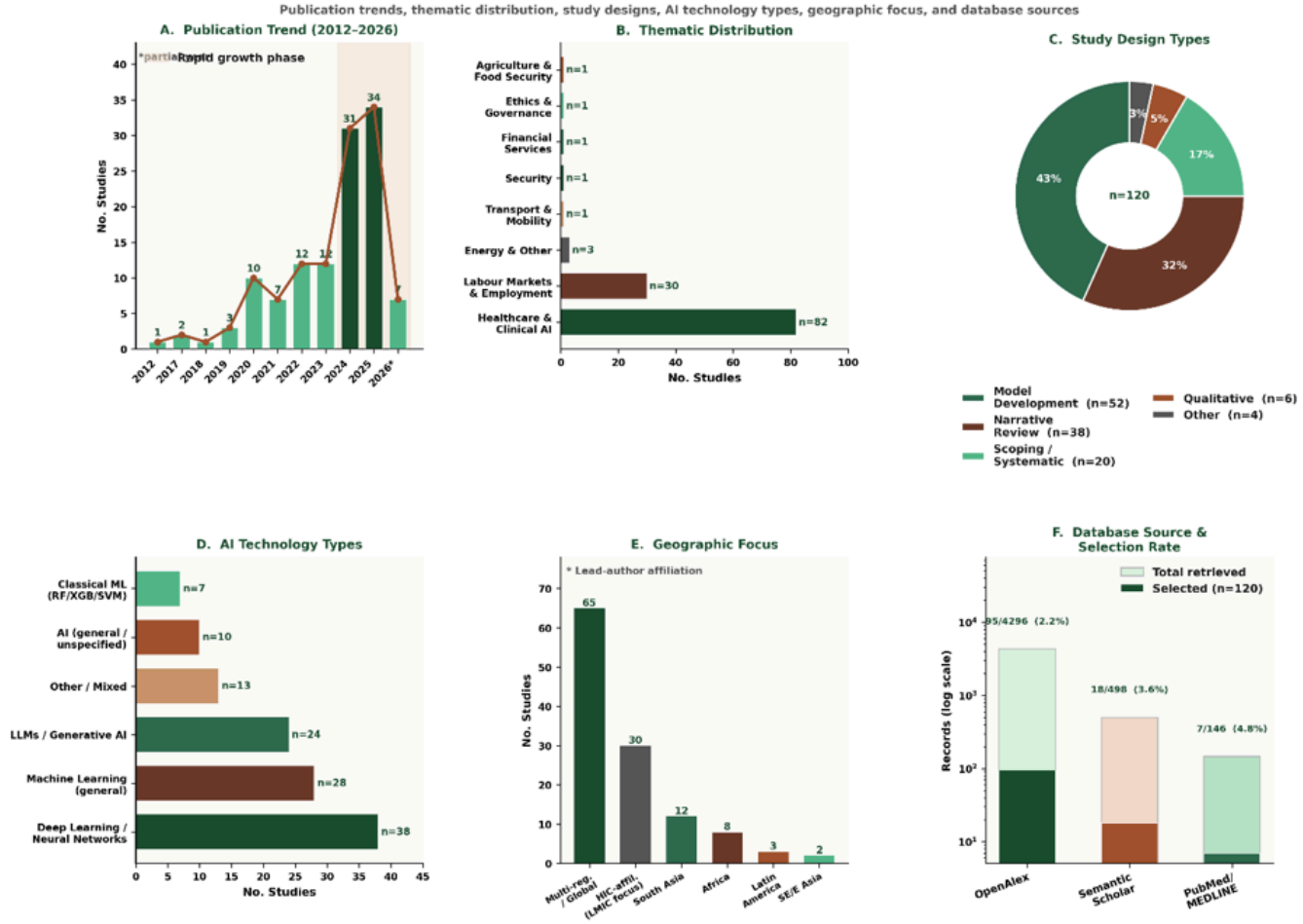


Figure 3

Bibliometric profile of included studies (*n* = 120)

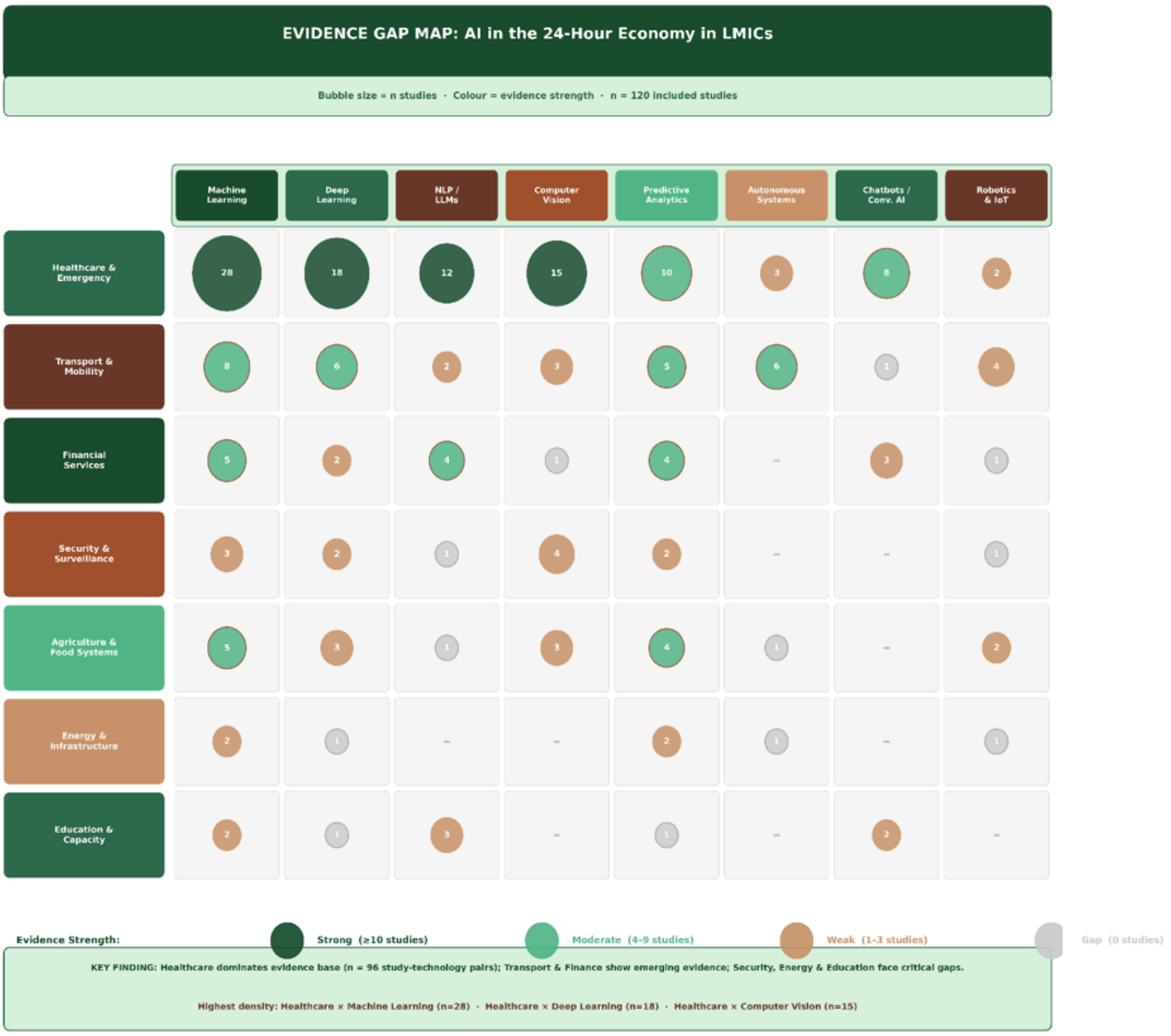


Figure 4

Bubble matrix showing evidence strength (colour) and volume (size) at each AI technology × sector intersection across 120 included studies

Unstructured Supplementary Service Data; ROI = Return on Investment.

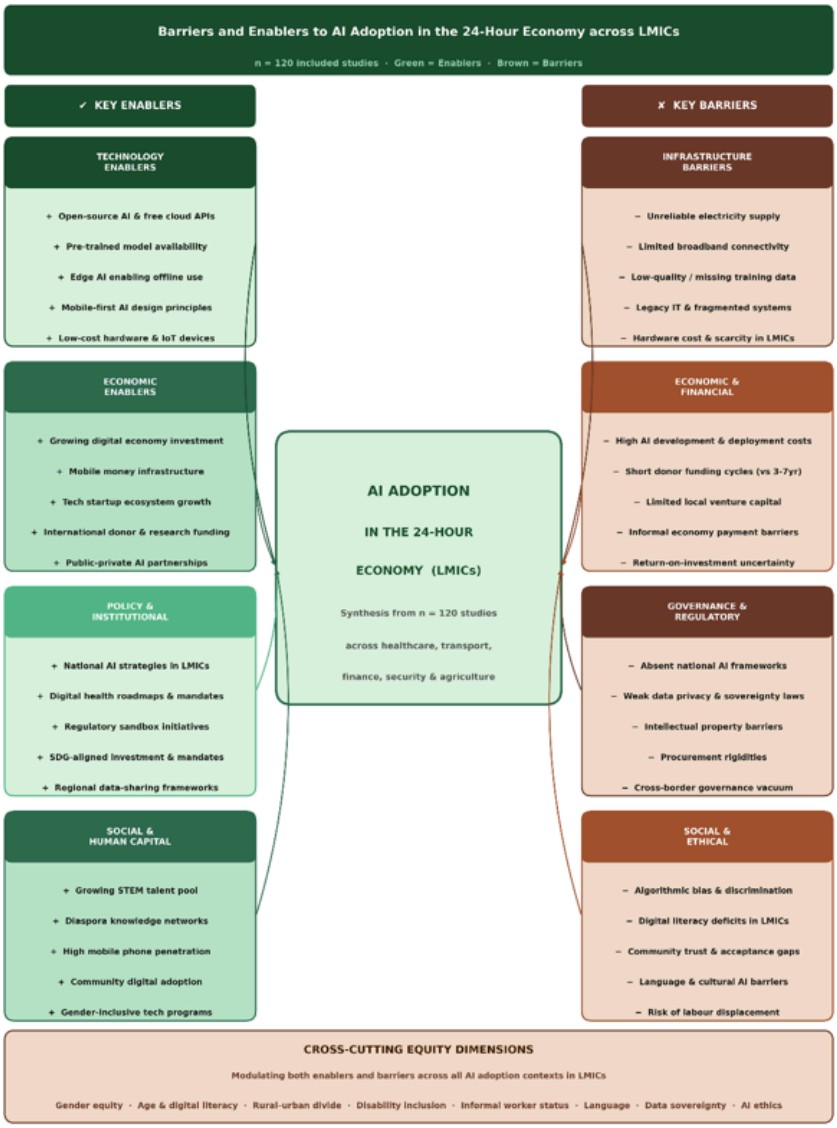


Figure 5

Structured framework showing key enablers (green cards, left) and key barriers (brown cards, right) across five domains, with cross-cutting equity lens footer.

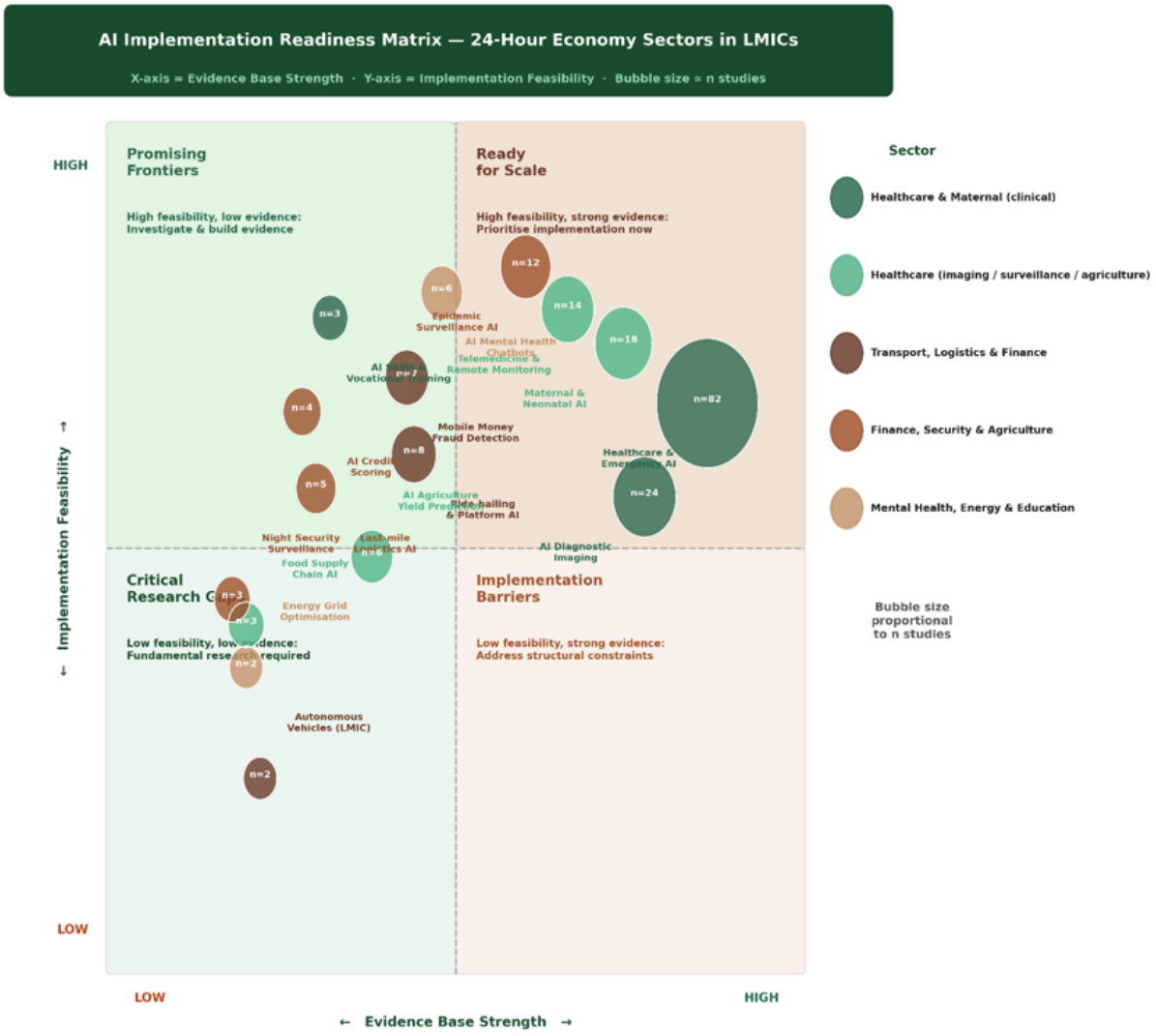


Figure 6

Quadrant plot mapping 16 AI-sector applications across evidence base strength (x-axis) and implementation feasibility (y-axis). Quadrants: Ready for Scale, Promising Frontiers, Implementation Barriers, Critical Research Gaps.