

From Burnout to Breathing Room: The Emerging Role of Artificial Intelligence in Healthcare Worker Well-being

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Abstract

Healthcare-worker burnout reflects heavy workloads, staffing shortages, administrative friction, and limited control. Artificial intelligence (AI) may ease pressures, but many African clinics use paper-based or hybrid records. The study examined AI-supported workload reduction and its relevance to ophthalmic and Nigerian practice. A structured narrative review examined peer-reviewed research and governance sources published between January 2024 and March 2026. Ambient AI scribes generally reduced perceived documentation burden, although evidence came mainly from electronic health record-enabled United States ambulatory settings and effects varied. Evidence for AI-supported mental-health care was limited. African sources instead highlighted paper records, fragmented systems, low electronic-record use, and constraints involving electricity, connectivity, financing, training, and interoperability. No study was identified that evaluated ambient AI and worker well-being in a predominantly paper-based African clinic. AI cannot replace records or organizational reform. African implementation should be affordable, offline-capable, prevent duplication, and directly measure well-being and equity. 150 words

Keywords: *Artificial intelligence; Burnout; Clinician well-being; Mental health; Africa; Paper-based records*

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Background to the Study

Burnout develops when the demands of work repeatedly exceed the time, resources, and control available to meet them. Its familiar signs - exhaustion, growing mental distance or cynicism, and reduced professional efficacy - are felt by individuals, but their consequences are dire to the health system (World Health Organization, 2019). For healthcare workers, burnout is associated with attrition, poorer work-life balance, and risks to the quality and safety of care. The National Academies therefore describes clinician burnout as a systems problem, not a failure of individual resilience (National Academies of Sciences, Engineering, and Medicine, 2019).

Studies use different instruments and thresholds, so prevalence estimates vary; nevertheless, the burden is consistently substantial (Rotenstein et al., 2018). The electronic health record (EHR) is one part of that story. When an EHR is difficult to use, it fragments attention, increases cognitive work, and pushes documentation into late hours and other time that should allow for recovery (Melnick et al., 2020). Evidence also suggests that organizational changes are generally more effective than approaches that leave individual clinicians to carry the full responsibility for coping (West et al., 2016). Studies conducted after the acute phase of the COVID-19 pandemic showed that burnout and dissatisfaction with work-life integration persisted, strengthening the need for structural responses (Shanafelt et al., 2022).

The entry of AI into this conversation became practical in everyday forms. Ambient scribes listen to clinical encounters and produce draft notes, while large language models prepare replies to patient messages or summarize information in the record (Duggan et al., 2025; Garcia et al., 2024; Hassan et al., 2025; Lukac et al., 2025; Ma et al., 2025; Misurac et al., 2025; Olson et al., 2025; Shah et al., 2025). Conversational systems have also been used to provide screening and coping support (Kleinau et al., 2024), while related digital outreach can connect workers to human care (Agarwal et al., 2024). These tools are often discussed together, but they tackle different pressures. A scribe aims to give back time and attention; a mental-health tool aims more directly at symptoms, coping, or access to care. Both, however, depend on the infrastructure through which care is documented and delivered. The African healthcare landscape deserves explicit attention. Nigeria's Federal Ministry of Health and Social Welfare reported in 2024 that most facilities still relied on paper-based records, while only a small number used EMR/EHR platforms (Federal Ministry of Health and Social Welfare, 2024). Across Africa, digital systems remain uneven because of gaps in electricity, connectivity, financing, interoperability, and workforce capacity (Bataliack et al., 2024; Mugauri et al., 2025). Ambient tools developed for mature EHR systems may therefore add printing, scanning, transcription, or reconciliation in paper and hybrid clinics. The relevant question is whether AI reduces total documentation work without creating a second record system.

The question that matters is not how quickly AI can generate text, but whether healthcare workers finish the day with less unfinished work and more capacity to think, recover, and remain present with patients. A tool may reduce typing while adding verification, consent

procedures, alerts, or pressure to see more patients (Altschuler et al., 2024; Hassan et al., 2025; Leung et al., 2025; World Health Organization, 2024). Paper-based clinics may also face printing, scanning, transcription, and duplicate entry. Manually locating paper folders consumes staff time and adds strain across the clinical team. This review therefore examines when AI reduces total work, when it shifts work elsewhere, and what that distinction means for Nigerian and similar health services.

Review objectives

1. To describe AI-enabled interventions intended to reduce administrative workload, cognitive burden, burnout, or psychological distress among healthcare workers.
2. To summarize reported effects on documentation time, after-hours EHR work, task load, burnout, work exhaustion, professional fulfilment, and mental-health outcomes.
3. To identify the safety, human-factors, ethical, and organizational conditions that determine whether efficiency gains translate into durable worker well-being.
4. To examine how paper-based, hybrid, and fully electronic record environments affect the feasibility, equity, and likely well-being impact of AI in African and Nigerian health services.

Methods

Design and eligibility

A structured narrative review was undertaken because the evidence covered different interventions, record environments, comparators, follow-up periods, and outcomes. Eligible sources included peer-reviewed reviews, trials, implementation studies, quality-improvement evaluations, and relevant policy or governance guidance. AI studies had to report a worker-level workload or well-being outcome. African contextual sources were included when they described paper, hybrid, or electronic record use and the infrastructure needed to judge transferability. Diagnostic, patient-only, educational, and technical-performance studies were excluded unless they directly informed implementation readiness.

Information sources and search strategy

PubMed/MEDLINE, Scopus, Web of Science, and Google Scholar were searched for publications dated 1 January 2024 to 31 March 2026. Terms covered AI, generative AI, large language models, ambient scribes, chatbots, healthcare workers, burnout, well-being, mental health, EHR and administrative burden, Africa, Nigeria, paper and hybrid records, digital readiness, electricity, and connectivity. Reference lists were examined, and targeted searches of WHO Regional Office for Africa and Nigerian Federal Ministry of Health sources provided policy context. Earlier landmark papers were retained when needed to explain burnout, ophthalmic documentation burden, or digital readiness.

Selection, extraction, and synthesis

Titles and abstracts were screened before full-text review. For AI studies, the extracted fields included setting, professional group, design, sample size, intervention, comparator, follow-

up, uptake, workload and well-being outcomes, findings, and limitations. For African sources, record type and constraints involving electricity, connectivity, affordability, interoperability, training, staffing, and governance were also recorded. The synthesis assessed whether AI reduced work, improved well-being, could function in paper or hybrid services, and required particular safeguards. Heterogeneity precluded meta-analysis; therefore, the direction, size, consistency, credibility, and transferability of effects were considered.

PRISMA reporting and table development

Relevant PRISMA 2020 principles guided reporting of the search, eligibility criteria, screening, data extraction, and narrative synthesis (Page et al., 2021). Because this was a structured narrative review rather than a registered systematic review or meta-analysis, pooled estimates and certainty grading were not undertaken. A flow diagram was not included because complete record-level search and exclusion counts were unavailable.

Table 1 summarizes representative AI studies and African digital-readiness evidence using predefined fields for design, setting, intervention or context, outcomes, and limitations; reported values were taken directly from source publications without pooling. Table 2 is an author-developed matrix linking AI functions and record environments with proposed mechanisms, outcome measures, and safeguards, informed by the included studies and WHO guidance (Bataliack et al., 2024; World Health Organization, 2024).

Ethics

The review used published and publicly available material and did not involve human participants or identifiable data; institutional ethical approval was therefore not required.

Results

Overview of the evidence

The evidence was recent, geographically narrow, and based largely on electronic care. Most AI reports were short US ambulatory pilots or quality-improvement studies of ambient documentation (Duggan et al., 2025; Hassan et al., 2025; Ma et al., 2025; Misurac et al., 2025; Olson et al., 2025; Shah et al., 2025). The strongest design was a randomized trial within one US health system (Lukac et al., 2025). Evidence on inbox drafting and direct mental-health support was limited (Agarwal et al., 2024; Garcia et al., 2024; Kleinau et al., 2024). African sources focused mainly on whether records and infrastructure were ready for such tools (Babatope et al., 2024; Bataliack et al., 2024; Federal Ministry of Health and Social Welfare, 2024; Mugauri et al., 2025; Olukorode et al., 2024). No evaluation of ambient AI and worker well-being in a predominantly paper-based African clinic was identified. Because designs, record environments, and outcomes differed, the evidence was synthesized thematically.

Table 1: Representative evidence on AI-enabled workload reduction, healthcare-worker well-being, and African digital readiness

Study	Design/setting	AI intervention	Main finding	Interpretation
Garcia et al., 2024	Prospective QI; 162 clinicians; US academic centre	EHR-integrated LLM drafts for patient inbox replies; 5 weeks	Mean draft use 20%. Reply time did not fall; task-load score decreased 13.87 points and work-exhaustion score 0.33 among paired respondents.	Perceived relief without measurable time saving; single centre and self-selected survey cohort.
Duggan et al., 2025	Pre-post QI; 46 clinicians; 17 specialties	Ambient AI scribe in outpatient practice	Note time per appointment fell from 10.3 to 8.2 min; same-day closure increased; after-hours work fell from 50.6 to 35.4 min/day.	No concurrent control; early-adopter and short-term effects.
Ma et al., 2025	Prospective QI; 45 physicians; 8 disciplines	LLM-powered ambient scribe; 3 months	Used in 55.3% of 17,428 encounters. Median time per note fell 0.57 min; daily documentation, after-hours, and total EHR time fell 6.89, 5.17, and 19.95 min.	Large variation between users; modest absolute time saving.
Shah et al., 2025	Prospective QI; 48 physicians; paired n=38	Ambient AI scribe; 3 months	Task load fell 24.42 points; burnout score fell 1.94; usability improved 10.9 points.	Volunteer sample; no control; outcomes mainly self-reported.
Misurac et al., 2025	Pre-post observational; 38 clinicians; paired burnout n=35	Ambient AI notes	Median burnout score improved from 4.16 to 3.16; prevalence fell from 69% to 43%. Lowest-use quartile did not improve.	A suggestive use-response pattern, but small and non-randomized.
Olson et al., 2025	Multicentre pre-post QI; 263 clinicians; 6 US systems	One ambient scribe platform; 30 days	Burnout prevalence fell from 51.9% to 38.8% (OR 0.26, 95% CI 0.13-0.54); cognitive task load and after-hours documentation also improved.	Largest multisystem evaluation; no randomized comparator and 60% paired-survey completion.
Lukac et al., 2025	Pragmatic 3-arm RCT; 238 physicians; 14 specialties	Two ambient AI scribes vs usual care; 2 months	One product reduced time-in-note 9.5% vs control; the other did not. Both produced modest favourable well-being changes. Clinically significant inaccuracies occurred occasionally.	Strongest causal design; one academic system, English encounters, modest uptake, secondary well-being endpoints.
Hassan et al., 2025	Systematic review	Clinical implementation of AI scribes	Documentation time and satisfaction often improved; adoption and performance varied, with major gaps in safety, organizational, equity, and long-term outcomes.	Early, heterogeneous evidence dominated by observational implementation studies.
Kleinau et al., 2024	2-arm RCT; 1,584 randomized health workers; Malawi	Interactive mental-health chatbot vs internet resources; 8 weeks	Difference-in-differences favoured the chatbot for depression (-0.68) and resilience (+1.47); estimates for	Substantial attrition and pandemic context, but directly relevant

Study	Design/setting	AI intervention	Main finding	Interpretation
			anxiety and burnout crossed the null.	African trial evidence.
Mugauri et al., 2025	Scoping review; 30 studies; sub-Saharan Africa	EHR implementation and readiness context (not an AI intervention)	Recurring barriers included infrastructure, power, connectivity, finance, privacy, interoperability, training, and double entry.	AI documentation evidence assumes a digital foundation that is uneven across the region.
Babatope et al., 2024	Cross-sectional study; staff at one Nigerian teaching hospital	EHR utilization and implementation context	EHR utilization was low; financial limitations and insufficient ICT resources were prominent barriers, with power and connectivity also implicated.	Single-centre evidence, but directly relevant to Nigerian readiness and implementation burden.
Olukorode et al., 2024	Review of five Nigerian primary studies	Introduction or improvement of EMR systems	EMR introduction or improvement increased data quality; evidence on patient outcomes and satisfaction was limited.	Foundational digitization may improve records, but the evidence base remains small and is not evidence of AI benefit.

Documentation Assistance can Reduce Job Demands

Ambient documentation was the most studied application. Early prospective studies reported less note time, after-hours EHR work, and cognitive load (Duggan et al., 2025; Ma et al., 2025; Misurac et al., 2025; Olson et al., 2025; Shah et al., 2025). Ma et al. (2025) found a median reduction of 0.57 minutes per note and 5.17 minutes of after-hours EHR time daily. Duggan et al. (2025) reported larger unadjusted reductions, although modelled estimates were smaller. These useful but modest gains reflect relief from EHR work and cannot be assumed to apply where clinicians still write, retrieve, and file paper records (Babatope et al., 2024; Bataliack et al., 2024; Federal Ministry of Health and Social Welfare, 2024; Mugauri et al., 2025).

Early well-being findings were encouraging but came mainly from uncontrolled studies. Shah et al. (2025) reported lower task load and burnout after three months. Misurac et al. (2025) found that burnout prevalence fell from 69% to 43%, with no improvement among the lowest users. Olson et al. (2025) reported a 13.1-percentage-point reduction after 30 days. Volunteer participation, incomplete follow-up, and short observation periods prevent firm causal conclusions.

The randomized trial by Lukac et al. (2025) was given greater weight because clinicians were assigned to one of two ambient products or usual care. Only one product reduced note time, although both modestly improved well-being. Relief may reflect less divided attention even when time changes little; inaccurate or poorly matched drafts may instead add strain.

Administrative drafting may reduce effort without saving time

AI-generated patient-message replies showed that time and mental effort are different outcomes. Clinicians used drafts for about one in five replies; task load and work exhaustion improved, but message-handling time did not (Garcia et al., 2024). Drafting may reduce initiation effort while adding review. However, this evidence assumes an EHR-linked portal and may not transfer to clinics using face-to-face communication, telephone, SMS, or informal messaging outside the clinical record (Bataliack et al., 2024; Federal Ministry of Health and Social Welfare, 2024; Mugauri et al., 2025).

The AI-scribe systematic review reached a similar conclusion: documentation time and satisfaction often improved, but adoption varied and evidence on safety, cost, equity, and durability remained incomplete (Hassan et al., 2025). Efficiency is therefore an implementation outcome, not an automatic property of the model.

Direct mental-health support is promising but under-evaluated

Very little evidence addressed AI used directly for psychological support. In Malawi, the Vitalk chatbot improved depression and resilience-related outcomes compared with passive internet resources, while confidence intervals for anxiety and burnout included no effect (Kleinau et al., 2024). Attrition was substantial, but the study included several health-worker cadres in an African setting with limited conventional support. This intervention did not require a mature EHR, although it still depended on device access, connectivity, privacy, language, cultural fit, and a dependable route to human care (Bataliack et al., 2024; Kleinau et al., 2024).

A US randomized trial of 1,275 healthcare workers tested proactive digital outreach rather than AI alone (Agarwal et al., 2024). Depression and anxiety improved modestly, but burnout and broader well-being did not. Its main lesson is that digital support should identify need and connect workers to human care rather than wait for exhausted staff to seek help unaided.

The African starting point is often paper-based or hybrid

Regional evidence changed the interpretation of the AI studies. Nigeria's health ministry reported that most facilities still used paper records (Federal Ministry of Health and Social Welfare, 2024), while the WHO Regional Office for Africa described fragmented health-information systems and uneven infrastructure and workforce capacity (Bataliack et al., 2024). Many clinics are therefore considering AI before their record environment is reliably digital.

A 2025 review of 30 sub-Saharan African EHR studies identified recurring problems with infrastructure, power, connectivity, finance, privacy, interoperability, training, and double entry (Mugauri et al., 2025). A Nigerian teaching-hospital study found low EHR use and prominent financial and ICT barriers (Babatope et al., 2024). Another Nigerian review found improved data quality after EMR introduction, but only five primary studies and little

evidence on patient outcomes (Olukorode et al., 2024). These findings support a staged approach: strengthen the record foundation, assess whether digitization reduces burden, and add AI only when it avoids duplicate work.

Implementation conditions and possible harms

Technology may shift work rather than remove it: typing becomes checking, or tasks move to nurses, records staff, administrators, and IT teams. Hybrid services may require the same encounter to be written, entered electronically, printed, scanned, or reconciled (Babatope et al., 2024; Bataliack et al., 2024; Mugauri et al., 2025). WHO guidance emphasizes accountability, privacy, transparency, stakeholder participation, and continuing evaluation (World Health Organization, 2024). AI-scribe risks include omissions, fabricated details, note bloat, automation bias, and medicolegal uncertainty (Leung et al., 2025). Clinicians need time to verify drafts, and institutions must identify the authoritative record (Altschuler et al., 2024).

The same caution applies to decision support. Poorly timed or repetitive alerts add noise, and alert fatigue reflects relevance, timing, design, and cumulative burden (Gani et al., 2025). A tool that increases interruption has not created breathing room.

Table 2: Interpreting an AI well-being intervention: mechanism, measure, and safeguard

AI function	Proposed mechanism	Outcomes to measure	Minimum safeguards
Ambient documentation	Less typing, recall, and divided attention	Time per note; after-hours EHR time; task load; burnout	Clinician review; specialty templates; error audit; consent and privacy controls
Inbox drafting or summarization	Less initiation and synthesis effort	Message time; editing burden; response quality; work exhaustion	Escalation rules; provenance; high-risk filters; accuracy and equity sampling
Predictive prioritization or alerts	Earlier identification and better work sequencing	Alert volume; acceptance; interruption cost; missed events	Clinical relevance thresholds; tiered alerts; user controls; alert-fatigue monitoring
Conversational mental-health support	Low-threshold screening, coping support, and navigation	Depression; anxiety; burnout; resilience; engagement; referral completion	Crisis pathways; clear limits; privacy; cultural and language validation; human care
Organizational deployment	Turns saved effort into recovery or meaningful clinical work	Work hours; schedule intensity; autonomy; retention; patient access	Protect saved time; avoid automatic quota increases; co-design; workforce and equity review
Paper-based or hybrid record setting	Digitize selected high-burden tasks without creating a second documentation pathway	Folder retrieval; transcription; printing/scanning; duplicate entry; downtime; data completeness; team workload	Offline capability; one authoritative record; patient identifiers; staged rollout; power and connectivity fallback; records-staff co-design

Discussion

Principal Findings

This review supports two conclusions. In EHR-enabled services, AI can reduce selected documentation burdens. In many African services, the more immediate problem is the absence of a reliable, interoperable electronic record (Babatope et al., 2024; Bataliack et al., 2024; Federal Ministry of Health and Social Welfare, 2024; Mugauri et al., 2025). AI cannot replace that foundation or correct staffing shortages, moral distress, inadequate resources, poor leadership, or loss of autonomy. It should be treated as one component of work redesign and digital development rather than a substitute for organizational reform or mental-health care.

Ambient scribes had the strongest evidence, with recurring improvements in note time, after-hours work, task load, burnout, and attention to patients (Duggan et al., 2025; Lukac et al., 2025; Ma et al., 2025; Misurac et al., 2025; Olson et al., 2025; Shah et al., 2025). However, effects differed between products and users, uptake was incomplete, follow-up was short, and all studies assumed an electronic record. The evidence does not show whether ambient tools reduce burden in paper clinics or create extra work during a hybrid transition.

Evidence for direct mental-health support was less mature. The Malawi trial provided encouraging evidence for depression and resilience, but not for every outcome or chatbot (Kleinau et al., 2024). Wider digital-engagement evidence suggests that proactive outreach and connection to human care may matter more than conversational sophistication (Agarwal et al., 2024). Mental-health AI should therefore remain an adjunct for screening, self-management, and navigation, supported by crises escalation and accessible human care.

Why outcomes are mixed

The findings were easier to interpret when record maturity was considered. In an EHR clinic, a draft must still be checked. In a paper clinic, it may also require printing, signing, filing, or transcription. In a hybrid clinic, outages can produce two incomplete versions of one encounter. Benefit therefore depends on accuracy, specialty fit, record maturity, electricity, connectivity, interoperability, training, records staffing, and a clear source of truth (Altschuler et al., 2024; Babatope et al., 2024; Bataliack et al., 2024; Duggan et al., 2025; Gani et al., 2025; Garcia et al., 2024; Hassan et al., 2025; Leung et al., 2025; Lukac et al., 2025; Ma et al., 2025; Misurac et al., 2025; Mugauri et al., 2025; Olson et al., 2025; Shah et al., 2025).

What happens to saved time matters as much as the minutes saved (Hassan et al., 2025; National Academies of Sciences, Engineering, and Medicine, 2019; World Health Organization, 2024). Throughput may rise without improving recovery or autonomy, while paper and hybrid services may lose gains to scanning, printing, correction, and duplicate entry. Breathing room exists only when net effort falls across the team and some benefit returns to patient care, recovery, learning, or finishing on time. Implementation should specify whose burden will fall and what error or added-work threshold will trigger redesign.

Implications for ophthalmology and Nigerian practice

Ophthalmology is suitable for careful, narrow deployment because high-volume clinics generate repeated notes, imaging reports, referrals, and patient instructions. In an EHR-enabled academic centre, ophthalmologists spent 10.8 minutes per encounter in the record, including substantial time outside clinic (Read-Brown et al., 2017). Paper-based eye clinics face different burdens, including retrieving prior notes and reconciling serial findings. AI should therefore be matched to the existing record pathway rather than imported as an EHR solution where no EHR exists.

In Nigerian services, paper records are central to feasibility. The health ministry reported in 2024 that most facilities still used paper-based methods (Federal Ministry of Health and Social Welfare, 2024). Regional and national studies describe fragmented systems, low EHR utilization, and constraints in infrastructure, power, connectivity, finance, privacy, interoperability, and training (Babatope et al., 2024; Bataliack et al., 2024; Mugauri et al., 2025). A tool that requires continuous broadband, cloud access, and structured historical data may therefore exclude the clinics under greatest pressure.

A practical Nigerian pathway may begin with reliable patient identifiers, digitized registers, searchable summaries, local templates, and offline capture. In paper clinics, voice-generated drafts may help with referrals, operative notes, and patient instructions if they enter the existing folder without duplicate transcription. Hybrid pilots should name one authoritative record, provide downtime procedures, fund hardware and support, and measure work transferred to nurses and records staff. Improved data quality after Nigerian EMR introduction is encouraging, but foundational digitization should be evaluated separately from AI (Olukorode et al., 2024).

Strengths and limitations

A strength of this review is that it connects workload reduction and mental-health support with the clinic's digital starting point. It distinguishes relief from EHR burden from the foundational work of building a usable record and considers whose workload may rise when a new digital layer is introduced.

This review has important limitations. The synthesis was narrative, and heterogeneity precluded meta-analysis. AI well-being studies came mainly from volunteer early adopters in US ambulatory systems, while African evidence addressed digitization and EHR readiness rather than AI and worker well-being (Babatope et al., 2024; Bataliack et al., 2024; Federal Ministry of Health and Social Welfare, 2024; Mugauri et al., 2025; Olukorode et al., 2024). The interaction between paper records and ambient AI therefore remains largely untested. Many AI studies lacked controls, relied on self-report, and had short follow-up. Commercial products change rapidly, unsuccessful implementations may be underreported, and findings cannot be transferred unchanged to Nigerian ophthalmic services.

Conclusion

AI may create breathing room, but not by the same route in every health system. EHR-enabled services may benefit from reduced documentation friction; many African clinics first need reliable identification, retrievable records, electricity, connectivity, trained staff, and interoperability (Babatope et al., 2024; Bataliack et al., 2024; Federal Ministry of Health and Social Welfare, 2024; Mugauri et al., 2025; Olukorode et al., 2024). AI should be introduced only when it reduces network and does not create a parallel record. In ophthalmology, this requires staged, locally tested, offline-capable tools, human verification, and clear ownership of the final record. An algorithm cannot solve burnout or compensate for a missing health-information foundation.

Recommendations

- i). Future studies should report whether clinics begin with paper, hybrid, or electronic records and measure burden across the full documentation chain.
- ii). African trials should include rural, primary, secondary, and specialist services and compare offline, locally hosted, and cloud-dependent tools.
- iii). Outcomes should include retrieval, transcription, duplicate entry, downtime, data quality, team workload, cost, equity, patient continuity, burnout, and professional fulfilment.
- iv). Mental-health trials also need culturally validated measures, local languages, crisis safeguards, active comparators, and representation of the wider health workforce.

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