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AI-POWERED CLINICAL DECISION SUPPORT SYSTEMS (CDSS): CREATING A NEW FORM OF DIAGNOSTIC DEPENDENCE IN PRIMARY CARE

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ABSTRACT

This paper critically examines diagnostic dependence – the tendency of clinicians to over-rely on AI-driven clinical decision support systems (CDSS) – in primary care settings worldwide. We define diagnostic dependence as a form of automation bias where clinicians accept machine guidance as a heuristic substitute for careful judgment [1][2]. The study explores causes (e.g. cognitive factors, workflow pressures, lack of experience), mechanisms (e.g. reduced vigilance, "cognitive offloading"), and consequences (new error types, skill erosion). A systematic review of human factors literature reveals that CDSS can introduce automation bias (AB), which arises when users "over-rely on decision support, reducing vigilance" [1]. Key mediators include clinician trust and confidence in the AI, individual cognitive style, workload and task complexity [3][4]. Drawing on recent global case studies and surveys, we document diagnostic-dependence concerns in diverse health systems: for example, surveys in the U.S. (where 66% of physicians use health-AI by 2024 [5]) show enthusiasm tempered by calls for training and oversight; focus groups in the U.K. report GP worries about accuracy and deskilling [6]; and studies in Saudi Arabia and China reveal usage rates

(~30%) and common fears of undermining clinical autonomy [7][8]. We compare system factors – such as interface design, regulatory regimes, and education policies – that shape diagnostic dependence. Finally, we discuss ethical and policy implications: mitigating over-reliance via clinician training in AI literacy, workflow redesign, accountability frameworks, and improved AI explainability and governance. Drawing on the latest research and expert guidelines (e.g. WHO's call for careful oversight [9]), we conclude with evidence-based recommendations to balance AI augmentation with human expertise, ensuring safe and effective care worldwide.

Keywords: Clinical Decision Support Systems (CDSS), Diagnostic Dependence, Automation Bias, AI Explainability, Cognitive Offloading, Workflow Integration, Skill Erosion, Accountability Frameworks.

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I. Introduction

AI-powered clinical decision support systems (AI-CDSS) are increasingly entering primary care to assist diagnosis and management. A CDSS is typically a software tool that "improve[s] healthcare delivery by enhancing medical decisions with targeted clinical knowledge and patient information" [10]. Modern AI-CDSS use advanced machine learning to analyze patient data (symptoms, labs, imaging) and generate patient-specific recommendations or risk assessments. In theory, AI-CDSS can augment clinicians by reducing errors, flagging rare conditions, or easing documentation, and thus help improve efficiency and outcomes [10][11]. In primary care – the front line of healthcare – AI-CDSS have been proposed for tasks such as triage, screening, diagnosis of common conditions, and preventive care. For example, automated symptom-checkers and predictive models are deployed in telehealth triage and ambulatory clinics. Many health systems have begun piloting or integrating AI tools in electronic health records (EHRs), and adoption is accelerating: a recent AMA survey found 66% of US physicians using some form of health AI in 2024, up sharply from 38% in 2023 [5]. However, concerns are mounting about unintended consequences. Even as AI-CDSS can improve diagnostic accuracy on average, they also change how clinicians reason. Of particular concern is diagnostic dependence, a phenomenon where clinicians come to over-trust or over-rely on AI guidance at the expense of their own critical judgment. This can manifest as failure to detect machine errors, neglect of additional clinical information, or deferring decisions wholly to the AI. In human factors literature, this tendency is known as automation bias (AB) – "the tendency to over-rely on automated cues as a heuristic replacement for vigilant information seeking and processing" [1]. CDSS are intended to assist clinicians, but they can also introduce new error pathways when used uncritically [12][13]. In extreme cases, reliance on AI-CDSS could erode clinicians' diagnostic skills (sometimes called AI-induced deskilling), undermining long-term capacity [14][6]. This paper takes a global, cross-system view of diagnostic dependence in AI-CDSS within primary care. We synthesize evidence from cognitive and informatics research on how AI support changes clinician behavior, focusing on early-career or overburdened practitioners who may be particularly susceptible. We then review real-world examples and case studies from diverse health systems (the U.S., U.K., continental Europe, Asia, Africa), highlighting both observed dependence problems and system responses. We compare how design, regulation, and education influence these dynamics across countries. Finally, we discuss ethical and policy implications, offering strategies (training, governance, design improvements) to mitigate diagnostic dependence. Our aim is a comprehensive, evidence-based critique of diagnostic dependence, written from a policy-oriented perspective and reflecting the latest research and global expertise in health AI.

II. Literature Review

Automation Bias and Clinical CDSS

The core psychological mechanism underlying diagnostic dependence is automation bias (AB). In the clinical context, AB occurs when clinicians accept a decision-support recommendation with insufficient scrutiny, leading to diagnostic omission (missing an un-alerted problem) or commission (acting on incorrect advice) [15]. In practice, clinicians may trust a CDSS suggestion even if their own assessment would differ. This reduction in vigilance is especially dangerous because AI systems are not perfect: they have false positives and negatives, and biases from training data. Users may not notice or question a flawed AI suggestion, so CDSS can introduce new errors even as they prevent others [16][17]. Studies show that AB is mediated by several factors. User-related factors include trust and confidence: if a clinician has high trust in the system, they are more likely to accept its advice without verification [3]. Cognitive style and experience matter too: novices or less experienced clinicians may lack confidence in their own judgment and thus defer more to the AI [3].

Environmental factors such as workload, time pressure, and cognitive load also exacerbate AB [3][4]. In a classic systematic review, Lyell and Coiera found that automation bias is not limited to multi-tasking scenarios, but is strongly associated with tasks of high verification complexity or cognitive demand [18]. When tasks are complex or clinicians are rushed, they may implicitly use the CDSS as a mental shortcut. A synthesis by Goddard et al. confirms these mediators: user factors (experience level, cognitive style), system factors (DSS design), and context factors (workload, time constraints) jointly determine AB's frequency [3]. Trust in the system (often driven by past success or marketing hype) and familiarity can promote over-reliance [3]. Conversely, training interventions and accountability mechanisms can mitigate AB: for instance, requiring clinicians to justify overrides or flagging low-confidence AI suggestions can increase vigilance [3]. The Goddard review highlights that interventions like better interface design (placing advice clearly, showing confidence levels, offering information rather than blunt recommendations) also help clinicians process AI output more critically [3]. Other lines of research emphasize related concepts like automation complacency: clinicians may become so assured of system reliability that they reduce monitoring of all data [19]. Parasuraman and Manzey have argued that complacency and AB are two sides of the same coin – both resulting from limited attention being captured by the automation [20][21]. In either case, the limited attentional resources of practitioners (particularly busy generalists) mean that introducing AI support shifts the diagnostic workflow, not always beneficially. For example, a practitioner might skip re-examining vital signs if an AI triage tool has already assessed them. Importantly, AB has been documented even when automation is only moderately reliable [22]. Lyell et al. note that "overreliance on less-than-perfect automation" can still cause decision errors [18]. Thus, even high-performing AI tools do not eliminate human oversight needs. Cognitive experiments in healthcare settings have repeatedly shown that users tend to accept computer suggestions despite obvious errors (if not prompted to verify), especially under stress or fatigue. Though much evidence comes from simulation studies, the human factors consensus is clear: any AI-CDSS integration must account for these predictable biases [23][4].

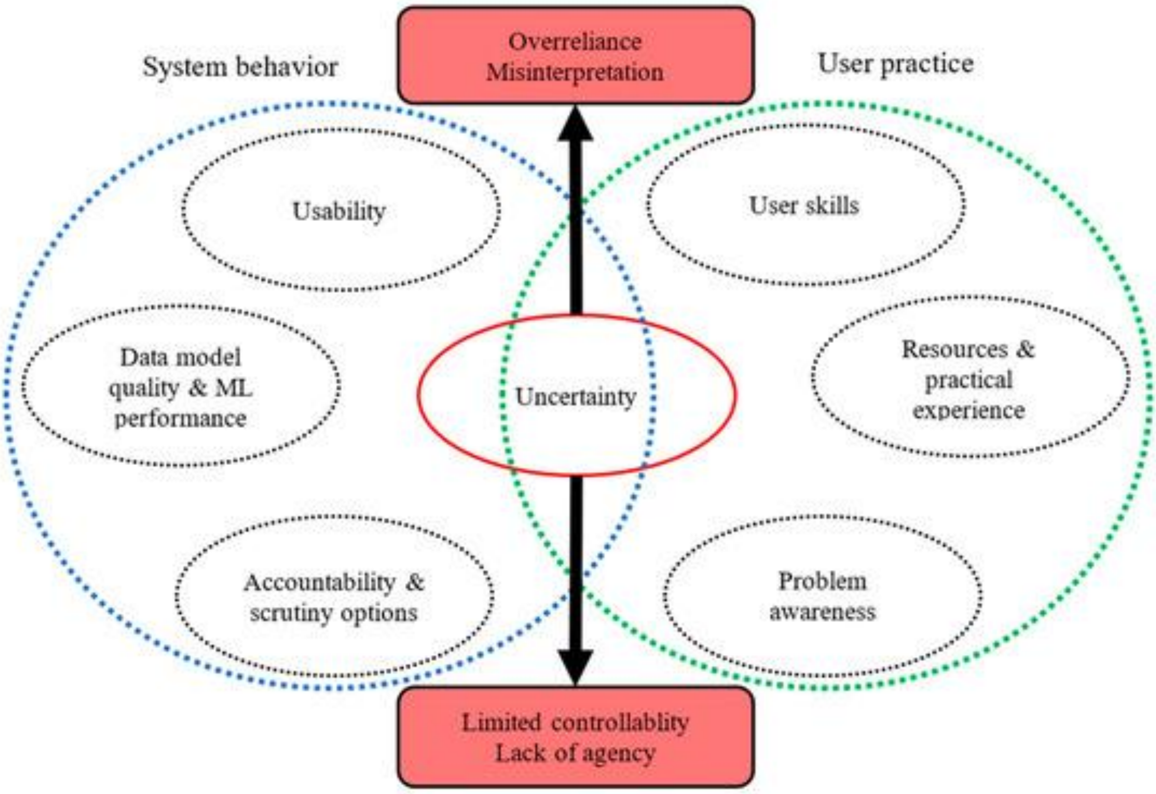

Figure 1. Main influencing factors of deep automation bias. Source - MDPI Journal, Volume 5, Issue 2

Diagnostic Dependence and Skill Changes

Beyond immediate AB, experts warn of longer-term shifts. The notion of deskilling describes loss of human expertise when tasks are automated. In medicine, if clinicians repeatedly rely on AI to filter or diagnose, they may train themselves to skip critical reasoning. A recent commentary notes that while AI can augment healthcare tasks, there is "the potential for a reliance on technology at the expense of human expertise" [24]. Similarly, a review on burnout and AI in healthcare observes that "the reliance on AI may diminish clinical skills, as continuous practice and hands-on experience are crucial for maintaining proficiency" [25]. This suggests that if a physician stops regularly performing certain diagnostic tasks (e.g. reading radiographs or reviewing symptoms) because AI does it, their own abilities may atrophy. However, some recent research on training with AI is reassuring. For example, a 2025 study of radiology residents found that an AI-based scoring tool actually reduced diagnostic errors and increased inter-rater agreement by 22% when incorporated into training [26]. Crucially, residents in that study still largely recognized and resisted AI errors above a certain threshold [26]. The authors emphasize that using AI as a collaborative tool (rather than a crutch) led to "upskilling" effects. They caution only that programs must balance "educational benefits and deskilling risks" [26] – for instance by ensuring residents also practice without AI aids. These results suggest that the risk of deskilling is context-dependent: good AI integration (with explanation and oversight) can support learning, whereas unchecked use may not.

Summary of Cognitive Shifts

In sum, the literature paints a complex picture. On one hand, AI-CDSS often improve average diagnostic performance and reduce simple errors, especially for rare or subtle conditions. But they introduce new cognitive shifts: clinicians may reduce information gathering and critical evaluation, particularly under stress or with high trust in the tool [3][4]. The concept of diagnostic dependence captures this shift. It is analogous to automation bias in other domains (aviation, nuclear power), but here applied to clinical diagnosis. If unchecked, diagnostic dependence can both cause immediate misdiagnoses and gradual erosion of physicians' judgment skills [14][6]. The severity of these effects depends on factors we will explore: clinician experience, system design, training, and healthcare context. Notably, most of this research is recent and evolving; yet it consistently underscores one lesson: AI-CDSS must be designed and managed with human cognition in mind, lest we undermine the very clinicians they aim to assist.

Mechanisms of Over-Reliance on AI-CDSS and Biases in AI lifecycle

This figure maps the stages of the AI model life cycle in healthcare, highlighting the common phase at which biases can be introduced. The AI life cycle is divided into six phases: conception, data collection, pre-processing, in-processing (algorithm development and validation), post-processing (clinical deployment), and post-deployment surveillance. Each phase is prone to specific biases that can affect the fairness, equity, and equality of healthcare delivery.

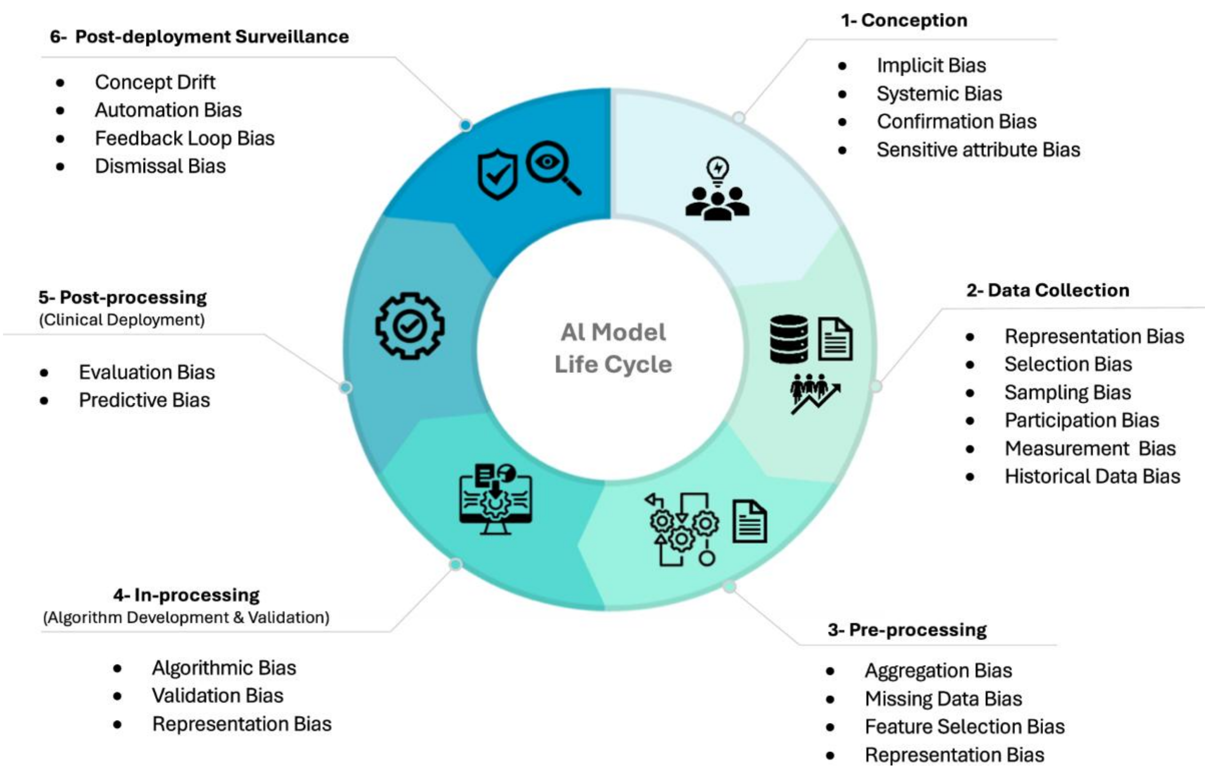

Fig. 3: The AI model life cycle and common biases across each phase. Source - NPJ Digital Medicine Journal, An overview of clinical decision support systems: benefits, risks, and strategies for success

AI-CDSS can foster clinician over-reliance through several intertwined mechanisms. We highlight the most important below, particularly how they affect early-career or overburdened practitioners.

Cognitive Load and Time Pressure: In busy primary care settings, physicians often juggle many patients and tasks under tight schedules. High workload and complexity consume attentional resources [3]. In such states, a clinician facing a long shift or queue of patients is more likely to accept AI suggestions as a shortcut. Lyell et al. found that automation bias correlates with the degree of cognitive load in diagnostic tasks [4]. When decision-tasks are complex, clinicians subconsciously delegate verification to the AI. If the CDSS reduces some burden (e.g. by automatically listing differential diagnoses), the clinician may inwardly rationalize that "the machine has it." This is especially true for routine or repetitive cases: after seeing many similar presentations, a fatigued doctor may default to the AI's output without double-checking.

Experience and Training: Less experienced clinicians (interns, juniors) have not yet internalized all diagnostic heuristics. They may find AI recommendations reassuring and assume the system has more expertise. This dynamic can create a vicious cycle of dependence: the novice relies on AI advice to "learn," but then misses opportunities to develop independent reasoning. Conversely, a fully confident and experienced doctor might use CDSS as one data point while still thoroughly verifying. Jung & Jung's UK study illustrates this concern: some GPs explicitly worried about "maintaining complex clinical skills" when AI begins to make diagnoses [6]. Training level also affects familiarity with technology. Inadequate AI education (lacking curriculum on when/why to trust AI) means young doctors may not know how to properly interrogate AI output. Thus early-career practitioners, despite being tech-savvy, can be cognitively vulnerable to over-trusting.

Trust and Perceived Authority: Clinician trust in AI-CDSS is a double-edged sword. Trust is necessary for adoption, but too much trust (or misplaced trust) amplifies reliance. If a CDSS has a reputation for accuracy, clinicians might adopt its suggestions implicitly. For example, if an AI system confidently recommends a diagnosis, a physician under uncertainty may defer to it even against contradicting evidence. Explainability influences this: clear explanations can increase trust [27], but ironically may also lull users into complacency. JMIR-AI research shows that when AI offers transparent reasoning, clinicians' trust in the output often increases [27]. If explanations appear coherent, users may assume the AI "must know best." Conversely, if the AI is a "black box", a cautious doctor might ignore it entirely. Achieving the right trust calibration (neither blind faith nor undue skepticism) is key [27]. Importantly, as discussed later, excessive trust in wrong AI advice can be just as dangerous as over-skepticism [27].

Design and Interface Factors: The way AI advice is presented can nudge clinicians toward dependence. For instance, a common design issue is alert fatigue: if a CDSS constantly presents pop-up alerts or recommendations, clinicians may quickly develop an "ok button" mentality, scrolling past without proper attention. Goddard et al. note that presentation matters: placing advice in prominent locations or using confidence markers can influence whether clinicians seek more information or not [3]. Similarly, systems that issue recommendations (e.g. "suspected pneumonia: prescribe antibiotic") rather than information (e.g. "symptom X suggests pneumonia, probability Y%") tend to encourage blind acceptance [3]. Early-career doctors, still learning, might rely on recommended actions verbatim. Poor interface design (cryptic alerts, lack of rationale, or overwhelming volume of advice) can thus inadvertently train clinicians to click-through.

Accountability and Responsibility: If a physician knows they remain legally responsible for a decision, they may be more careful to validate AI input. Conversely, unclear accountability can shift blame dynamics. In some settings, AI-CDSS use is experimental, whereas in others it is deployed as a "standard of care" tool (as with some diagnostic imaging aids). Where the culture implicitly or explicitly endorses the AI's authority, clinicians might feel pressure to conform. Weiner et al. report physicians' need for a "feedback loop" and clear guidelines on oversight [11]. Without explicit standards, individual judgment may give way to AI signals. For example, a primary care doctor might document, "treated per CDSS suggestion," even if their own suspicion differed, assuming that insulates them from liability. This phenomenon of shifting accountability fosters over-reliance.

Socio-Technical Context: Systemic factors also play a role. In settings with less clinical support (e.g. understaffed rural clinics) or where telehealth is widespread, clinicians may rely more on AI for second opinions. Socioeconomic factors such as resource constraints can thus pressure reliance: one might trust AI to triage patients when specialist access is limited. The QUALMAT project in Africa, for instance, found that overworked midwives in rural clinics actually accepted and continuously used eCDSS for maternal care, helped by training, even though unreliable power and extra work were barriers [28]. That case shows how necessity (scarce alternative expertise) can increase dependence on CDSS if the system is well-supported.

In summary, diagnostic dependence arises from a confluence of cognitive, educational, design, and systemic elements. Overload and inexperience make clinicians lean on automation; trust and interface design determine how that reliance manifests; and broader contexts (workforce, policy) shape the opportunity and perceived need to use AI. Importantly, these factors are modifiable. As we will discuss, interventions like improved AI literacy, better CDSS design, and institutional guidelines can address many of these mechanisms.

III. Global Case Studies of Diagnostic Dependence

To understand how diagnostic dependence plays out in reality, we examine reports and studies from diverse health systems. While comprehensive case reports are still scarce, several insights emerge from recent literature and field experiences.

United States

In the U.S., primary care is increasingly adopting AI-CDSS tools, often within EHR systems or as third-party apps. The aforementioned AMA survey (2025) found that 66% of physicians report using AI for tasks like documentation, discharge summaries, or diagnostic support [5] – a dramatic jump from the prior year. This rapid uptake highlights both enthusiasm and risk. On one hand, many U.S. GPs and internists have embraced AI for mundane tasks, hoping to reduce burdensome paperwork. On the other hand, some studies flag concerns about over-reliance. For example, an advisory report notes that while doctors see potential for increased diagnostic accuracy, they also emphasize training and oversight needs [5]. Almost half of surveyed US physicians ranked increased regulatory oversight as the top action needed to build trust in AI tools [5]. This suggests an awareness of dependency risks: clinicians want guardrails so that AI remains an assistant, not a replacement. Concrete examples in the U.S. include decision support integrated into EHRs for imaging or lab ordering. For instance, many EHRs now alert for drug interactions or sepsis risk. Surveys of EHR-based CDSS users indicate mixed experiences: some appreciate the catch of hidden issues (like a medication allergy alert), while others report override fatigue. Although not specifically documented as "diagnostic dependence," these workflow anecdotes show the tension: do doctors train themselves to memorize drug interactions, or do they let the system do it? Early-career US physicians working in high-volume clinics have noted that heavy reliance on EHR alerts sometimes leads them to miss issues when the system fails or is offline. In rural telemedicine pilots (e.g. AI-enabled triage in telehealth for opioid prescription or mental health), there are concerns that non-specialist providers might second-guess the AI less critically, though peer-reviewed data on these effects are just emerging. In summary, in the US primary care setting, diagnostic dependence is a live concern. Strong AI adoption (as reflected in the AMA data) is contrasted by calls for education and governance [5]. System-level factors (like a push for AI-enabled EHRs) may be fueling dependence, but surveys show clinicians asking for safeguards. This suggests the U.S. is at a tipping point: large-scale deployment of AI-CDSS is underway, but stakeholders recognize the need to prevent over-reliance.

United Kingdom and Europe

In the U.K., the National Health Service (NHS) has experimented with AI-CDSS in both primary and secondary care. One prominent pilot was the NHS "GP at Hand" service, which used an AI chatbot for triage (provided by a company Babylon). Although Babylon claimed its AI diagnostic scores matched doctors', the service eventually faced criticism for overestimating AI capabilities and was wound down, illustrating a real-world cautionary tale. More formally, NHS Digital's 2023 AI code of conduct emphasizes that AI must support – not replace – clinical judgment. Qualitative research captures British GPs' attitudes: a 2023 PLOS One workshop study found that London GPs identified maintaining clinical skills and AI error accountability as major concerns [6]. They specifically worried about "preventing AI errors" and the impact on skill retention [6]. This echoes sentiments that over-dependence on AI could erode the diagnostician's role. Similarly, European surveys indicate physicians want evidence that AI tools are safe and effective before trusting them. Regulatory frameworks in the EU (such as the impending AI Act) are explicitly aimed at preventing misuse, though guidelines on dependence are not yet fully articulated. In practice, some European countries have introduced AI-CDSS in primary care. For example, in parts of Scandinavia and the Netherlands, GPs use CDSS for antibiotic stewardship or early disease screening. These systems often come with mandatory documentation steps, encouraging clinicians to think through decisions even when an AI suggestion is present. However, anecdotal reports suggest that younger physicians trained with these tools occasionally admit relying heavily on the software, then wonder if they could make decisions unaided. European professional societies are thus emphasizing that AI advice should be interpretable: one UK health regulator notes that if clinicians do not understand how an AI reached its conclusion, they should not over-trust it (as part of their professional duty).

Asia (Middle East and East Asia)

In Asia, both highly developed and rapidly developing health systems are adopting AI-CDSS, but with different challenges. A recent large survey in Saudi Arabia (2025) found that about 31.6% of primary care professionals reported using AI tools in practice, mostly for diagnostic support (59.5% of users) [7]. This indicates moderate adoption. However, the respondents voiced significant concerns: nearly half feared that AI could undermine the "human touch" in care, and many pointed to reliability issues [7]. This mix of moderate use and strong concern illustrates diagnostic dependence risk: when clinicians do use AI, they remain wary of blind trust. In China, AI-driven CDS has seen rapid research investment. A 2025 study of Chinese hospitals found that factors like workload and perceived threat to autonomy strongly influence physicians' willingness to adopt AI-CDSS [8]. Notably, doctors in primary care settings (vs. tertiary hospitals) reported time constraints and autonomy concerns as barriers [8]. These are exactly the conditions that would make them prone to either ignore AI (because they distrust it) or overuse it out of desperation. China also has pilot programs in rural areas (e.g. AI triage in village clinics), but technology gaps and limited training may ironically leave practitioners either ignoring AI or following it uncritically. Elsewhere in Asia, Singapore and Japan are experimenting with AI-support for chronic disease management in primary care. In many of these contexts, high patient volumes and dense healthcare systems can pressure over-reliance. For example, if a densely scheduled clinic uses an AI to pre-screen every patient's notes for red flags, doctors may become habituated to only focus on what the system highlights. Cultural factors also play a role: in some settings, there is a high trust in technology, which could amplify dependence if unchecked. Conversely, where systems are new and clinicians skeptical, they might under-utilize the CDSS.

Africa (Sub-Saharan)

In many African countries, digital health is growing, but infrastructure and resources are limited. Pilot projects like the QUALMAT program (Tanzania and Ghana) and others have introduced electronic CDSS for maternal and child health in rural clinics. The QUALMAT experience is instructive: their eCDSS for antenatal care was successfully adopted – health workers used it continuously and accepted the recommendations for maternal care [28]. Key enablers were training and regular support [28]. However, challenges like unreliable power and increased workload were noted [28]. Importantly, despite these challenges, the system's usage did not drop off: the report explicitly says most challenges did not substantially hinder use [28]. This suggests that even under resource constraints, once clinicians rely on a CDSS (to improve patient care), they will do so persistently. Whether this counts as "harmful dependence" is unclear: the goal was good patient care, and they got it with CDSS support. But it raises questions: if an African midwife is on duty and the eCDSS goes offline (power failure), can she revert to older methods? Or has she become "dependent" on the tool for decision cues? Thus, the African case is double-edged. On one hand, it shows that CDSS can be embraced and very useful in low-resource primary care (a success). On the other, it highlights that when systems are scarce, clinicians might not have the luxury to second-guess AI: they trust it to fill gaps in expertise. Given that training was a key enabler [28], this also underscores how capacity-building (training clinicians to use and interpret CDSS) can mitigate harmful dependence by ensuring users are empowered, not passive.

IV. System-Level Factors: Design, Regulation, and Education

Diagnostic dependence is not only an individual cognitive issue; it is profoundly shaped by system-level factors. We analyze three domains – system design, regulatory/policy environment, and education/training – comparing how they influence dependence globally.

System and Software Design

The way CDSS are designed and integrated into workflows can either encourage or discourage over-reliance. Important design considerations include:

Advice Presentation: CDSS can be advisory (presenting information) or directive (giving recommendations). Directive advice (e.g. "Treat as pneumonia") tends to promote reliance, whereas informational output ("75% probability of pneumonia based on symptoms") encourages clinician evaluation. Goddard et al. emphasize that systems presenting recommendations (vs. just info) can increase automation bias [3]. Designing the UI to require active engagement (e.g. clinicians must click to reveal the answer, or compare the AI's confidence level) can make users think twice. Including explanations or evidence references (XAI principles) can also modulate trust [27].

Alert and Notification Policies: Over-notification (too many alerts) leads to habituation. Best practices suggest tiering alerts by severity and limiting non-critical prompts. If clinicians can customize alerts (e.g. silence low-level suggestions), they may avoid "always on" mode. However, disabling alerts can also risk missing important cues. It is a design challenge to strike a balance. Some countries have begun guidelines for alert management: for instance, the US Office of the National Coordinator for Health IT recommends user-centered design of EHR alerts to avoid fatigue.

User Control and Override: Systems should be designed to make overriding the AI recommendation straightforward yet not trivial. Requiring a brief justification or a simple checkbox for an override can reduce automated acceptance. In airline autopilots, pilots must sometimes manually re-engage systems to maintain alertness; similarly, forcing a small manual interaction can keep a doctor cognitively engaged.

Integration with Workflow: How seamlessly the AI tool fits into the care process matters. Standalone or separate interfaces may be more easily ignored or de-prioritized. Embedding AI suggestions directly in the EHR chart at the time of decision encourages use. For example, an AI that automatically flags abnormal vitals as soon as the nurse enters them may be more readily heeded than one requiring the doctor to open a separate app. Yet, seamless integration can also make the tool feel like part of the doctor, making it harder to separate human versus AI roles. Ensuring the system highlights when it is "advising" vs. "diagnosing" can help maintain clinician agency.

Transparency and Explainability: Providing explanations can build appropriate trust, but overly complex justifications can confuse. The literature finds that quality of explanation is key [27]. Ideally, AI-CDSS should show how they reached a conclusion (e.g. which inputs weighed most). This could mitigate blind trust by prompting clinicians to question suspicious reasoning. In Europe, the Medical Device Regulation (MDR) already requires a level of transparency for software; some regulators argue that black-box AI should not be used in critical decisions without human-understandable rationale.

These design factors differ in implementation globally. For instance, some EU and North American EHR vendors have built-in decision trees and clear evidence links, while other systems (in parts of Asia or Africa) may use simpler rule-based prompts. Mobile telemedicine apps often use chat interfaces for AI triage; this novel UX might influence reliance differently than desktop forms. In every context, designers must consider human cognitive tendencies: for example, placing AI prompts between patient history and final diagnosis (rather than at the very end) may prompt better clinical integration.

Regulation and Governance

Regulation can either deter or inadvertently encourage over-reliance. Key regulatory issues include:

Classification of AI-CDSS: Many jurisdictions now classify AI-CDSS as medical devices. In the EU, the AI Act and MDR will apply, requiring rigorous validation. In the US, the FDA has begun approving certain AI algorithms (e.g. for stroke detection), with the requirement that the clinician retains responsibility. Strict regulation can reassure users of the system's safety, but it can also create a false sense that "if it's approved, it must be correct." This paradox means regulators and policymakers should not only test AI performance, but also mandate guidelines on user training and monitoring for misuse.

Accountability Frameworks: Laws and professional regulations define who is accountable if an AI-aided decision is wrong. If liability is unclear, clinicians might over-rely (feeling that the AI is "to blame" for errors) or under-rely (to avoid blaming themselves). For instance, if a doctor fears legal consequences for ignoring an AI alert, they may comply blindly. Conversely, knowing they will be held responsible encourages verification. Some countries (e.g. Germany) are explicitly clarifying that physicians remain liable for their decisions, even when using AI tools, as part of professional duty to exercise judgement. This should theoretically counter excess trust, but it is most effective when clinicians are aware of it and confident in their skills [6].

Data and Training Regulations: If regulations enforce high standards for training data quality (e.g. requiring representative datasets), the resultant AI may have more consistent performance, reducing the risk of "surprise" errors that could trap clinicians. Regulatory bodies could also require post-market surveillance of AI-CDSS, so that patterns of over-reliance can be detected. For example, if a deployed AI is found to cause systematic overrides by clinicians, that feedback should be used to update guidance.

Guidelines and Codes of Practice: Beyond hard laws, professional guidelines influence culture. The NHS code of conduct for AI emphasizes AI as supportive, not authoritative. Ethics boards (like JME commentary) argue that care standards should reflect the highest level of expertise available – i.e., if AI is the best guess, doctors still need to consider alternatives.

Advocacy groups, like the WHO, have called for transparency and evaluation, warning that "precipitous adoption of untested systems" can erode trust and harm patients [9]. Such statements carry weight with policymakers. In practice, however, enforcement is variable: some health systems mandate AI-ethics committees, others do not.

Regulatory differences also emerge by region. The U.S. is moving fast with approvals (e.g. CMS reimbursement for certain AI tools) but has patchwork oversight. Europe tends to have stricter pre-market controls, though enforcement of safe use is still catching up. In China, the government is actively promoting AI in health, but their regulations on clinician-AI collaboration are evolving. In low-resource settings, regulation is often minimal, so NGOs and implementers have greater influence over CDSS standards (as with the QUALMAT project's emphasis on training [28]). Ultimately, good governance should ensure not only that the AI works, but that the socio-technical system (people + machine) works safely.

Education and Clinical Training

Perhaps the most powerful lever is training and education. If clinicians are taught about both the benefits and pitfalls of AI-CDSS, diagnostic dependence can be mitigated. Key strategies include:

AI Literacy Curriculum: Medical education should cover AI fundamentals: how algorithms work, common biases, and what constitute valid evidence of performance. Training students and residents to "look behind" an AI suggestion is crucial. For example, incorporating case studies (like scenarios where AI is wrong) can prepare them to question outputs. This approach can build calibrated trust – teaching clinicians to view AI as one data point, not the sole authority.

Simulation and Hands-On Practice: Just as pilots train on simulators, clinicians could train with AI tools in simulation. This lets them experience how AI can err and how to catch it, without risking patients. The radiology resident study [26] is a model: residents practiced cases both with and without AI, learning to balance reliance. Embedding AI use in continuing medical education (CME) ensures practicing doctors update their skills. Conversely, ignoring AI in training (leaving it as a "for techies" topic) risks leaving many clinicians unprepared for its pitfalls.

Reflective Practice and Peer Review: Encouraging clinicians to review cases where AI advice was used can surface dependence issues. For example, morbidity-and-mortality (M&M) conferences could include segments on AI-related errors (e.g. "we missed X because we trusted the AI"). Peer discussion of AI use patterns fosters awareness. Some hospitals already review

AI override rates: if a clinician never overrides a particular alert, that might trigger a coach to check their understanding.

Multi-Disciplinary Teams: Especially in settings with heavy AI-CDSS use, having teams of clinicians, IT specialists, and ethicists can provide oversight. These teams can set institutional policies (e.g. "AI suggestions should be second-checked for patient cases with red flags") and develop quick-reference guidelines. For instance, after an AI dermatology tool was introduced in a European clinic, the hospital created laminated "AI Usage Protocols" reminding doctors to do a physical exam regardless of the AI score. Such practical reminders help maintain professional responsibility.

Patient Engagement: Educating patients about AI use can indirectly reduce provider over-reliance. If patients know an AI is involved, they may be more inclined to ask questions or seek a second opinion, effectively adding another check. In one Australian study, patients were more satisfied when doctors explained an AI's recommendation in simple terms, suggesting that informed patients can hold clinicians accountable for due diligence.

Overall, robust training transforms the clinician from a passive "button-pusher" into an informed partner of AI. Many professional bodies now advocate adding AI to medical curricula. However, this is uneven globally: some elite institutions have begun courses in clinical AI, while others (especially in LMICs) have not. International guidelines (e.g. WHO's digital health frameworks) are starting to call for AI competency standards. Until these are widespread, gaps in training will remain a major driver of diagnostic dependence.

V. Ethical and Policy Implications: Mitigation Strategies

The phenomenon of diagnostic dependence raises significant ethical and policy issues. If left unaddressed, over-reliance on AI-CDSS could compromise patient safety, exacerbate inequities, and undermine the patient-clinician relationship. We outline key implications and propose strategies.

Patient Safety and Autonomy: At its core, diagnostic dependence affects the clinician's capacity to deliver safe care. Ethically, physicians are obliged to use all available evidence, including their own judgment. If a doctor abdicates this responsibility by mindlessly accepting AI output, the patient's autonomy (to have a true expert opinion) is undermined. Policies should reinforce that AI is a tool for supporting judgment. For example, clinical guidelines can explicitly state that AI suggestions should be considered, not definitive diagnoses. Regulatory bodies might require that patient records note both the AI's input and the clinician's independent reasoning, ensuring accountability.

Professional Accountability and Legal Standards: The legal system needs to clarify liability in AI-augmented decisions. One approach is to hold the clinician accountable for failure to critically assess AI. Professional guidelines (e.g. from medical boards) could specify that reliance on AI does not reduce the doctor's duty of care. Training on these guidelines would reinforce responsible use. Meanwhile, policymakers could incentivize the reporting of AI-related adverse events (just as there are error-reporting systems for drugs). This would create a feedback loop: identifying patterns of diagnostic errors tied to AI and responding systemically (e.g. issuing alerts or updating algorithms).

Equity and Access: Over-reliance might paradoxically widen health disparities. Wealthy health systems may have safeguards (redundant checks, skilled workforce) that mitigate AI errors, whereas resource-limited settings may not. For example, if an African clinic's only doctor blindly accepts an AI's diagnosis due to workload, whereas a U.S. hospital has a team second-guessing the AI, the outcomes differ. Policy must ensure equity: international guidelines (like WHO's) emphasize that AI should be "transparent, fair and inclusive" [9]. This means validating AI-CDSS across diverse populations so clinicians don't default to "the machine knows best" under uncertainty. It also means training should be tailored to context: in LMICs, emphasis might be on resilience to tool failures.

Regulation of Design Standards: Ethics demand that CDSS be designed to minimize harm from misuse. Standards organizations (e.g. ISO, IEEE) are developing AI ethics frameworks. These could become regulatory norms: for example, requiring human-centered design that explicitly assesses the risk of over-reliance. Before approving an AI-CDSS, regulators could ask: what measures does the developer have to prevent blind trust? The AMA and IEEE have issued recommendations for AI in healthcare that include user education and monitoring of usage patterns. Translating these into enforceable rules would help.

Transparency and Public Trust: Ultimately, medical AI must be transparent enough to maintain public trust. If patients or clinicians lose confidence in AI because of high-profile errors (and with it, trust in healthcare), everyone suffers. A policy-driven tone suggests we need proactive oversight. For instance, hospitals could publish summary data on CDSS effectiveness and error rates. National health authorities might convene AI ethics boards (as Singapore and the UK have done) to review new AI-CDSS before deployment. These bodies would consider not only accuracy but also the potential for diagnostic dependence and propose mitigations.

Training and Certification Requirements: On the educational front, policymakers could require certification in digital health for licensing. For example, after some years of use, doctors might need to demonstrate proficiency in AI-CDSS use (perhaps via simulation tests). This would institutionalize the idea that AI competence is integral to clinical competence. Continuing Medical Education (CME) programs could offer modules on "AI in practice" that count toward recertification. Funding agencies could prioritize research into clinician-AI interaction to develop best practices, thus informing policy.

Collaborative Governance: Given the cross-disciplinary nature of AI-CDSS, mitigating diagnostic dependence calls for collaboration among stakeholders. Governments, healthcare institutions, AI developers, and patient groups should jointly develop guidelines. For example, an EU consortium might produce a "Safe AI Diagnosis Charter" that member states adopt. In the U.S., partnerships between CMS, FDA, and medical societies could create standardized protocols for AI oversight. International bodies like WHO can issue frameworks (as they have for digital health) that nations tailor to their systems.

In summary, the policy response must be multifaceted. Technology alone cannot solve diagnostic dependence; we need rules of practice, education mandates, and design standards. Ethically, the priority is preserving clinician judgment and patient safety, while still harnessing AI's benefits. A useful analogy is aviation: autopilots are ubiquitous, but pilots are rigorously trained to monitor them and to intervene when needed. Medicine must similarly ensure that physicians remain fully engaged drivers of care, with AI as a copiloting aid – not as an "auto-drive" that clinicians unthinkingly engage.

VI. Conclusion and Recommendations

This paper has explored the complex phenomenon of diagnostic dependence on AI-CDSS in primary care worldwide. We have seen that while AI tools hold great promise for enhancing diagnosis and reducing routine errors, they also introduce new human-machine dynamics. Clinicians – especially those who are less experienced or under heavy pressure – may fall into automation bias, relinquishing vigilance and critical thinking to the AI system [1][3]. Evidence from cognitive studies confirms that high workload and trust amplify this bias, leading to omission and commission errors. Case studies from the U.S., U.K., Asia, and Africa illustrate both adoption trends and clinician anxieties: across continents, practitioners express enthusiasm about AI's potential, yet simultaneously fear skill erosion and accountability gaps [6][7][5]. Key lessons emerge. First, diagnostic dependence is not an insurmountable outcome of AI deployment; it is mitigable through deliberate strategies. Second, a systems approach is essential: designers must craft AI-CDSS with human factors in mind; regulators must enforce standards and training; medical educators must instill AI-savvy practices. Third, policies should frame AI-CDSS as augmentative tools – they should augment and not supplant clinician reasoning. Where implementation has succeeded (such as the maternal care eCDSS in Ghana/Tanzania [28]), a combination of clinician training, technical support, and awareness of challenges proved effective.

Recommendations: We conclude with expert-level recommendations to address diagnostic dependence:

1. Implement AI Literacy Training: Integrate AI-CDSS training into medical curricula and CME. Teach clinicians about automation bias, AI limitations, and strategies for critical evaluation of AI output.
2. Design User-Centered AI-CDSS: Require developers to follow human-centered design guidelines. Systems should clearly distinguish advice from raw data, allow easy override with justification, and present uncertainty/confidence levels. Integrate explainability where feasible to help clinicians understand AI reasoning.
3. Establish Governance and Oversight: Regulatory bodies should mandate reporting and review of AI-CDSS usage. For example, track override rates or error patterns. Create certification for AI tools that includes usability assessment, not just algorithm accuracy.
4. Mandate Accountability: Clarify that clinicians retain responsibility for diagnostic decisions, even when using AI. Professional codes should emphasize double-checking AI suggestions, especially in ambiguous cases.
5. Monitor and Audit: Healthcare institutions should monitor how often clinicians rely on AI vs. follow their own judgments, and audit outcomes. Adverse events linked to AI reliance should trigger reviews and system improvements.
6. Global Equity Measures: In low-resource settings, ensure AI-CDSS deployment is accompanied by robust training/support and infrastructure (power backup, local validation of AI). Aid and funding for digital health should include long-term training plans.
7. Collaboration and Standardization: Encourage international collaboration on AI-CDSS safety standards (e.g. through WHO, OECD). Share best practices and data on AI use in different healthcare contexts to continuously refine guidelines.

By taking these steps, health systems can harness the benefits of AI while safeguarding clinician expertise. Diagnostic dependence need not become a universal pitfall; with proactive policy and design, AI can truly serve as a partner, not a crutch, to primary care practitioners. Our analysis underscores that only a multifaceted, policy-driven response will ensure AI-CDSS amplify, rather than diminish, the quality and safety of global primary care.

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References

[1] Automation bias and verification complexity: a systematic review - PMC

[2] Automation bias: a systematic review of frequency, effect mediators, and mitigators | Journal of the American Medical Informatics Association | Oxford Academic

[3] Automation bias: a systematic review of frequency, effect mediators, and mitigators | Journal of the American Medical Informatics Association | Oxford Academic

[4] Automation bias: a systematic review of frequency, effect mediators, and mitigators | Journal of the American Medical Informatics Association | Oxford Academic

[5] AMA Augmented Intelligence Research | AMA

[6] Implementation challenges of artificial intelligence (AI) in primary care: Perspectives of general practitioners in London UK | PLOS One

[7] Artificial Intelligence in Primary Care Decision-Making: Survey of Healthcare Professionals in Saudi Arabia - PMC

[8] Journal of Medical Internet Research - The Willingness of Doctors to Adopt Artificial Intelligence–Driven Clinical Decision Support Systems at Different Hospitals in China: Fuzzy Set Qualitative Comparative Analysis of Survey Data

[9] WHO calls for safe and ethical AI for health

[10] An overview of clinical decision support systems: benefits, risks, and strategies for success | npj Digital Medicine

[11] Automation bias and verification complexity: a systematic review - PMC

[12] Automation bias and verification complexity: a systematic review - PMC

[13] Balancing act: the complex role of artificial intelligence in addressing burnout and healthcare workforce dynamics - PMC

[14] Automation bias and verification complexity: a systematic review - PMC

[15] Automation bias and verification complexity: a systematic review - PMC

[16] Automation bias and verification complexity: a systematic review - PMC

[17] Automation bias and verification complexity: a systematic review - PMC

[18] Automation bias and verification complexity: a systematic review - PMC

[19] The "Tech-Tonic Shift": The Deskilling Dilemma of Artificial Intelligence (AI) Transforming Healthcare

[20] Upskilling or deskilling? Measurable role of an AI-supported training for radiology residents: a lesson from the pandemic | Insights into Imaging | Full Text

[21] Upskilling or deskilling? Measurable role of an AI-supported training for radiology residents: a lesson from the pandemic | Insights into Imaging | Full Text

[22] Automation bias and verification complexity: a systematic review - PMC

[23] JMIR AI - How Explainable Artificial Intelligence Can Increase or Decrease Clinicians' Trust in AI Applications in Health Care: Systematic Review

[24] JMIR AI - How Explainable Artificial Intelligence Can Increase or Decrease Clinicians' Trust in AI Applications in Health Care: Systematic Review

[25] AMA Augmented Intelligence Research | AMA

[26] Promising adoption of an electronic clinical decision support system for antenatal and intrapartum care in rural primary healthcare facilities in sub-Saharan Africa: The QUALMAT experience - PubMed

[27] JMIR AI - How Explainable Artificial Intelligence Can Increase or Decrease Clinicians' Trust in AI Applications in Health Care: Systematic Review

[28] WHO calls for safe and ethical AI for health

[29] Upskilling or deskilling? Measurable role of an AI-supported training for radiology residents: a lesson from the pandemic | Insights into Imaging | Full Text

[30] Exploring the risks of automation bias in healthcare artificial intelligence applications: A Bowtie analysis - Peeref

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