Readiness to Adopt Artificial Intelligence and Big Data Analytics in Primary Health Care for Chronic Disease Management: A Narrative Review with Implications for Saudi Arabia

Abstract: *Non-communicable diseases account for most deaths in Saudi Arabia, and primary health care (PHC) centres carry the main responsibility for their detection and control. Artificial intelligence (AI) and big data analytics (BDA) are promoted as tools for risk stratification, screening and population health management, but their value depends on whether health systems are ready to adopt them. To synthesise evidence on the value of AI and BDA for chronic disease management in primary care and on the individual, organisational, technological and environmental factors that shape readiness to adopt them, with attention to Saudi Arabia and Al Madinah. A narrative review of peer-reviewed literature and official policy documents, focusing on 2019-2026, was conducted using the Technology Acceptance Model and the Technology-Organisation-Environment framework as the analytic lens. Bibliographic details and key findings of all cited sources were checked against publisher or official records. The strongest evidence of benefit concerns AI-supported diabetic retinopathy screening, including a randomised trial showing higher screening completion. For risk prediction, apparent advantages of machine learning over conventional models largely disappear in low-bias comparisons, external validation is rare, and few randomised trials exist, none reported from the Gulf. Professionals' attitudes are positive but conditional; Saudi studies report high trust or perceived usefulness alongside limited knowledge, high fear of replacement and low use (around 26-32%). Organisational factors, including leadership, culture, training and financing, and technological factors, notably incomplete EHR coverage, data quality and interoperability, emerge as the main constraints. Saudi Arabia has established national AI strategy, ethics principles, data protection law and device guidance, but evidence on how these reach PHC is limited, and no study of AI or BDA readiness among practising PHC professionals in Al Madinah was identified. Readiness, rather than algorithmic capability, is the binding constraint on AI and BDA adoption in PHC. Context-specific, theory-based readiness assessment combining individual and organisational dimensions is needed to guide safe and sustainable adoption in Saudi health clusters.*

Keywords: artificial intelligence; big data analytics; primary health care; organisational readiness; technology acceptance model; technology-organisation-environment framework; chronic disease; Saudi Arabia.

1. Introduction

Non-communicable diseases (NCDs) are the dominant cause of death and disability in Saudi Arabia. They were estimated to account for 73% of all deaths in 2016, with cardiovascular disease alone responsible for 37% (World Health Organization [WHO], 2018), and for 67.4% of disability-adjusted life-years lost in 2019 (Boettiger et al., 2023). Population ageing is projected to raise the cost of managing priority NCDs from USD 19.8 billion in 2020 to USD 32.4 billion in 2030 (Boettiger et al., 2023). National surveys also show large detection and control gaps. In 2013, 57.8% of Saudis with diabetes were undiagnosed and only 16.6% were treated and controlled (El Bcheraoui et al., 2014). In the 2019 World Health Survey, measured raised blood pressure affected 24.5% of adults and

obesity 22.0% (Ministry of Health [MoH], 2019), while treatment coverage among adults aged 30–79 with hypertension was 47.6% (MoH, n.d.). These gaps are visible in the setting of interest. In a study of 692 adults with diabetes attending 15 primary care centres in Al Madinah, only 15.7% achieved an HbA1c below 7% and 46.4% reached the LDL-cholesterol target (Alfadhli et al., 2025), although these data were collected in 2016–2017 and may not reflect current performance. Primary health care (PHC) centres are the first point of contact for this population and carry most of the responsibility for screening, risk stratification, follow-up and long-term control of chronic disease. Under Vision 2030, the Health Sector Transformation Program has reorganised MoH services into 20 integrated health clusters built around a prevention-oriented model of care, and has scaled national digital platforms such as Sehhaty, Seha Virtual Hospital and the NPHIES data-exchange platform (Health Sector Transformation Program, 2023).

Artificial intelligence (AI) and big data analytics (BDA) are increasingly proposed as tools for closing these gaps. Autonomous AI for diabetic retinopathy screening has met prespecified accuracy endpoints in primary care (Abràmoff et al., 2018), maintained performance in a national screening programme (Ruamviboonsuk et al., 2022), and increased screening completion in a randomised trial (Wolf et al., 2024). Machine-learning (ML) models built on electronic health record (EHR) data have reported higher discrimination for cardiovascular risk than conventional scores (Liu et al., 2025), and BDA has shown moderate-to-high accuracy for predicting diabetes complications (Borges do Nascimento et al., 2021). Yet this promise is contested. In comparisons at low risk of bias, ML shows no performance advantage over logistic regression (Christodoulou et al., 2019), few AI tools have been tested in randomised trials (Plana et al., 2022), and widely deployed proprietary models have performed poorly on external validation (Wong et al., 2021). The binding constraint for PHC is therefore less the existence of capable algorithms than the readiness of health systems, organisations and professionals to adopt, integrate and govern them. Saudi evidence suggests that this readiness is uneven. Only 150 of 2,259 PHC centres had an implemented EHR system in a recent national study, and lack of training (83.8%) and inadequate infrastructure (78.5%) were the most frequently cited barriers (Alzghaibi & Hutchings, 2025). Among Saudi PHC professionals, 47.2% reported being unfamiliar with AI and 31% reported using it (Alsudairy et al., 2025). Most AI-readiness research, in Saudi Arabia and internationally, has been conducted in hospitals, and only 14.1% of AI studies relevant to primary care included an author with a primary care appointment (Kueper et al., 2020).

In this review, AI refers to computational systems that perform tasks associated with human judgement, including ML and deep-learning models for prediction, classification and image interpretation, natural language processing, and rule-based expert systems. BDA refers to the integration and analysis of large, heterogeneous health datasets (EHRs, laboratory systems, registries, claims and device data) to generate population- and patient-level insight. In PHC the two are usually coupled: predictive models depend on data pipelines, and population analytics increasingly embed ML. Mapping studies confirm this overlap. Of 90 AI studies in community-based primary care, 45% used ML, 27% natural language processing and 19% expert systems (Abbasgholizadeh Rahimi et al., 2021). Because professionals rarely distinguish the two in practice, readiness studies often measure them jointly, a pragmatic choice that limits inference about technology-specific readiness. TAM proposes that perceived usefulness (PU) and perceived ease of use (PEOU) shape intention and use of a technology (Davis, 1989). In Davis's validation studies, PU correlated more strongly with usage ($r = .63$ and $.85$) than PEOU ($r = .45$ and $.59$), and PEOU appeared to act partly through PU. A review of TAM in health care concluded that the model "predicts a substantial portion of the use or acceptance of health IT" but that several relationships were inconsistent and the model needed context-specific additions (Holden & Karsh, 2010). A later systematic review of 134 health informatics studies found that TAM was commonly extended with constructs such as self-efficacy,

compatibility, training and facilitating conditions, and that no optimal health-specific version had emerged (Rahimi et al., 2018). Two critiques are central to AI. First, TAM explains intention better than objectively measured use (Turner et al., 2010). Second, for clinical AI, usefulness and perceived risk may outweigh ease of use: in a study of a diagnostic decision-support system, PEOU did not significantly predict intention ($\beta = 0.108$, $P = .07$), whereas perceived risk did ($\beta = -0.579$) (Zheng et al., 2025). The Unified Theory of Acceptance and Use of Technology (UTAUT), which adds social influence and facilitating conditions, explained up to 70% of variance in intention in its validation (Venkatesh et al., 2003) and underpins several recent AI acceptance studies (Lambert et al., 2023).

TOE locates adoption in the firm rather than the individual: the characteristics of the technology, the organisation's structure, resources and leadership, and the external environment of regulation, competition and partners jointly shape adoption (Tornatzky & Fleischer, 1990). TOE has been applied to AI and BDA in health care with consistent results. In Malaysian health organisations, technology, organisation and environment factors each contributed to big data adoption readiness (Ghaleb et al., 2021). Hierarchical analyses of AI service adoption identified data-leakage risk, low awareness of value, weak leadership support and government policy as root factors (Yang et al., 2022). In Finland, 82 experts rated organisational challenges, especially limited finances, insufficient AI competence and inadequate change management, as the most critical (Pulkkinen et al., 2025). A Saudi expert-weighting study likewise gave organisational criteria the highest weight (0.51), ahead of environmental (0.27) and technical (0.22) criteria (Kumar et al., 2025b). Weiner (2009) defines organisational readiness as a shared psychological state combining change commitment (members value the change) and change efficacy (members believe they can implement it, given task demands, resources and situational factors). The Organizational Readiness for Implementing Change (ORIC) measure operationalises these two factors with high reliability ($\alpha = 0.88–0.92$), although it was validated outside health care (Shea et al., 2014). Applied to AI, readiness has been framed around needs assessment, workforce acceptance, technology–organisation alignment and financing (Alami et al., 2021). The NASSS framework adds a complexity perspective across seven domains, from the condition and technology to the wider context and adaptation over time. Programmes with complexity in several domains "rarely, if ever, became mainstreamed" (Greenhalgh et al., 2017), and a NASSS-guided study of AI in a Canadian academic centre identified missing legal and governance frameworks and unclear business models as barriers (Alami et al., 2024). These frameworks explain why favourable individual attitudes may not translate into sustained organisational use.

Available instruments measure different levels. MAIRS-MS assesses individual readiness across cognition, ability, vision and ethics (22 items, $\alpha = 0.87$), but it was developed with medical students and its ethics subscale is weaker ($\alpha = 0.632$) (Karaca et al., 2021). It has been applied to Saudi nursing students, who reported high readiness (mean 3.79) (Bakarman et al., 2025). At the organisational level, an e-health readiness model for Polish PHC providers identified strategic, competence, cultural, structural and technological dimensions in a survey of 371 facility managers (Kruszyńska-Fischbach et al., 2022). No validated instrument was identified that measures AI or BDA readiness for PHC across TAM and TOE dimensions among practising professionals, which is the measurement gap the proposed study targets. This narrative review synthesises evidence on the readiness of PHC to adopt AI and BDA for chronic disease management and public health, with particular attention to Saudi Arabia and Al Madinah. It addresses four questions: (a) what AI and BDA have demonstrably delivered for NCD management in primary care; (b) which individual, organisational, technological and environmental factors shape readiness to adopt them; (c) what is known about these factors in Saudi PHC; and (d) which gaps remain that a context-specific readiness framework should address. The Technology Acceptance Model (TAM) and the Technology–Organisation–Environment (TOE) framework are used as the organising lens.

2. Methods

A narrative (critical) review was chosen because the question spans heterogeneous bodies of evidence that cannot be pooled: diagnostic-accuracy and prediction studies, randomised trials, attitude surveys, implementation studies, theoretical work and national policy documents. A narrative design permits theory-led interpretation across these sources but does not provide the reproducibility or exhaustiveness of a systematic review, and it is not reported as one. Searches were conducted in October 2026 through academic search engines and indexing services covering PubMed/MEDLINE records, publisher platforms (JMIR, BMC, Frontiers, MDPI, Elsevier, Springer Nature, Wiley, JAMA Network), DOAJ and institutional repositories, supplemented by official sources from the WHO, the Saudi MoH, the Health Sector Transformation Program, the Saudi Food and Drug Authority (SFDA) and the Saudi Data and Artificial Intelligence Authority (SDAIA). Search terms combined three concept blocks: (1) artificial intelligence, machine learning, deep learning, predictive analytics, big data analytics; (2) primary health care, primary care, general practice, family medicine, chronic disease, diabetes, hypertension, cardiovascular, obesity, population health; and (3) readiness, acceptance, adoption, perception, attitude, barrier, technology acceptance model, technology–organisation–environment, organisational readiness, implementation, with the additional terms Saudi Arabia, Gulf, Madinah. Reference lists of key reviews were scanned for further sources. Priority was given to peer-reviewed systematic reviews, meta-analyses and primary studies published from 2019 to 2026, with foundational theoretical works retained regardless of date. Sources were included when they reported (a) the performance or effect of AI or BDA for NCD management or population health; (b) factors associated with readiness, acceptance or adoption of AI, BDA or closely related digital health technologies among health professionals or organisations; or (c) Saudi epidemiological, policy or digital-infrastructure context. Commentaries were used only for conceptual points. Sources published in outlets without evident peer review, or whose bibliographic details could not be confirmed, were excluded.

The bibliographic details and principal findings of every cited source were checked against the publisher page, DOI record, official document or an index record. Figures are reported as stated in those sources. Formal risk-of-bias appraisal was not performed; instead, evidence was weighted by design (randomised and prospective evaluations and systematic reviews above cross-sectional surveys and commentaries), and design limitations are stated where findings are discussed. Findings were organised thematically using the TAM and TOE dimensions. Converting this work into a systematic or scoping review would require a registered protocol (PROSPERO or OSF), reproducible database-specific search strings run in PubMed, Scopus, Web of Science, CINAHL and the Saudi Digital Library with recorded dates, duplicate independent screening, a PRISMA 2020 (or PRISMA-ScR) flow diagram with actual counts, and design-appropriate appraisal (for example, the Mixed Methods Appraisal Tool or JBI checklists). None of these steps is claimed here.

3. Results

3.1 Value of AI and BDA and the Evidence-to-Practice Gap

The strongest evidence of benefit in primary care concerns diabetic retinopathy screening. An autonomous AI system tested prospectively in US primary care offices with 900 people with diabetes achieved 87.2% sensitivity and 90.7% specificity (Abràmoff et al., 2018). In Thailand's national programme, a deep-learning system screened 7,940 patients across nine primary care sites in real time, with 91.4% sensitivity and 95.4% specificity for vision-threatening disease (Ruamviboonsuk et al., 2022). The ACCESS randomised trial moved beyond accuracy to a care-process outcome: eye-

examination completion within six months was 100% with point-of-care autonomous AI versus 22% with usual referral (Wolf et al., 2024). These findings matter for Saudi PHC because diabetic retinopathy affects up to 40% of patients with diabetes in the country and, as of 2023, no national screening programme had been established (Barakat et al., 2023). For cardiovascular risk, a meta-analysis of 20 studies using EHR data reported pooled AUCs of 0.865 for random forest and 0.847 for deep learning, against 0.765 for conventional risk scores, but heterogeneity exceeded 99% and publication bias was possible (Liu et al., 2025). Reviews of AI for diabetes describe applications across prevention, imaging, monitoring, predictive modelling and decision support (Khalifa & Albadawy, 2024), and reviews of CVD risk prediction emphasise both potential gains and unresolved validation and interpretability problems (Kasartzian & Tsiampalis, 2025). For population health, an overview of 35 systematic reviews found that BDA showed moderate-to-high accuracy for diagnosing and predicting diabetes complications, but confidence was critically low in 25 of the reviews, and building well-structured, secure and standardised data sources was the most common challenge (Borges do Nascimento et al., 2021). In Saudi Arabia, AI has been applied to disease prediction, resource management and outbreak monitoring during mass gatherings such as Hajj (Kumar et al., 2025a). Taken together, the evidence supports a plausible but unevenly demonstrated value proposition: benefit is best established for image-based screening and least established for prediction models that require integration into routine chronic care.

Several syntheses temper claims of superior performance. Across 71 studies, ML showed no discrimination advantage over logistic regression in comparisons at low risk of bias (difference in logit AUC 0.00), whereas the apparent advantage appeared only in comparisons at high risk of bias (Christodoulou et al., 2019). For incident hypertension, pooled C-statistics were 0.75 for regression and 0.76 for ML (Chowdhury et al., 2022). For diabetes complications, ML gains were "generally modest", only 8% of 36 studies reported external validation, and 59% had high risk of bias (Ghafoor et al., 2026). Prospective evaluation remains rare: a systematic review identified 41 randomised trials of ML interventions, half of them single-site and none fully adherent to CONSORT-AI (Plana et al., 2022), and a later review of 65 AI trials found 37% conducted in China and 18% in the United States, with none reported from the Gulf (Martindale et al., 2024). Deployment failures show why local readiness matters. A widely implemented proprietary sepsis model achieved an AUC of 0.63 on external validation and missed 67% of sepsis cases (Wong et al., 2021). A commercial population-health algorithm underestimated the needs of Black patients because it predicted cost rather than illness; correcting it would raise the share of Black patients flagged for extra help from 17.7% to 46.5% (Obermeyer et al., 2019). Models also degrade when populations, practice or data capture change between development and deployment (Finlayson et al., 2021), and in Thai clinics an accurate retinopathy model met workflow problems when image quality and local conditions did not match its thresholds (Beede et al., 2020). Primary care has been largely absent from the development process: only 14.1% of 405 AI studies relevant to primary care had an author with a primary care appointment (Kueper et al., 2020). These findings imply that readiness includes the capacity to validate, monitor and govern models locally, not merely to acquire them.

3.2 Determinants of AI and BDA Readiness

3.2.1 Individual Readiness: Perceptions, Acceptance and AI Literacy

International syntheses describe health professionals' attitudes as broadly positive but conditional. Across 27 stakeholder studies, clinicians accepted AI "provided certain safeguards were met", with privacy breaches and personal liability for AI-related error as leading concerns (Scott et al., 2021). An integrative review of 42 hospital studies found that fear of losing professional autonomy and difficulty integrating AI into workflows were consistently reported barriers, while training facilitated

acceptance (Lambert et al., 2023). Among nurses, a review of 37 studies described "guarded optimism" with moderate literacy, concern about deskilling, and sustained knowledge gains after targeted training (El Arab et al., 2025). Primary care evidence is thinner and more sceptical. UK general practitioners regarded empathy and communication as exclusively human and considered AI's potential limited (Blease et al., 2019), German GPs' views clustered around concerns, expectations, environmental influences, individual characteristics and minimum system requirements (Buck et al., 2022), and a review of qualitative primary care studies highlighted the physician–patient relationship, workload, privacy, bias and the need for co-design (Martínez-Martínez et al., 2025). At the same time, informal use is growing: 20% of surveyed UK GPs reported using generative AI tools in clinical practice (Blease et al., 2024), which raises governance questions that readiness assessments rarely capture.

Saudi and Gulf studies reproduce a characteristic pattern of positive attitudes, limited knowledge and low use. In Riyadh hospitals, employees showed a general lack of knowledge about AI and a high fear of being replaced (Abdullah & Fakieh, 2020). In a national sample of 1,026 providers, 73.3% believed AI would replace them (Elnaggar et al., 2023). Among Saudi physicians, 82.1% trusted AI-based decision-making but only 25.9% had used AI in the previous year (Alhazmi, 2025), and the same use rate was reported among Jeddah hospital physicians (Alkhatieb & Subke, 2024). Among 250 Saudi primary care professionals, 47.2% were unfamiliar with AI tools, 31.6% used them, and high implementation cost (49.2%) and lack of training (34%) were the leading barriers (Alsudairy et al., 2025). Nurses in Saudi government hospitals held open but conservative attitudes, with differences by gender, age and education (Abuadas, 2024). By contrast, family physicians in Qatar's primary care corporation largely saw AI as augmenting rather than replacing their role (Waheed & Liu, 2024), and in the UAE trust and perceived benefit predicted acceptance, which in turn strongly predicted readiness ($\beta = .874$) (Alsalloum et al., 2026). These findings support the TAM premise that perceived usefulness and trust matter, but they also show a persistent intention–use gap that individual attitudes alone do not explain.

3.2.2 Organisational Readiness: Leadership, Culture, Skills and Resources

Organisational factors recur as the decisive layer. In 40 German hospitals, 90% of IT decision makers expected AI to be relevant to their institution, yet lack of staff, knowledge and finance was the main barrier, and few tools had reached routine care (Weinert et al., 2022). Supportive culture and leadership that built a coherent innovation narrative enabled AI integration in a Canadian academic centre (Alami et al., 2024). In Polish PHC, strategy shaped competence (path 0.686) and culture (0.664), and culture shaped structure (0.744) and technology readiness (0.388) (Kruszyńska-Fischbach et al., 2022). In Indian hospitals, organisational culture was strongly associated with PEOU ($\beta = 0.739$) and trust in AI ($\beta = 0.481$), and trust predicted self-reported actual use ($\beta = 0.527$) (Rathore et al., 2026), although that study has reporting inconsistencies. In Saudi big data adoption, BDA literacy, business–IT alignment and decision-making culture were organisational enablers, and resistance to change and public-sector funding dependencies were key challenges (Almoosa, 2025). Resistance to change also weakened the path from intention to actual use of BDA in health care (Shahbaz et al., 2019). Workforce development is part of this layer: an umbrella review of 108 systematic reviews identified training, incentives and perceived effectiveness as facilitators and workload as a barrier to digital health use (Borges do Nascimento et al., 2023).

3.2.3 Technological Readiness: EHRs, Data Quality and Interoperability

AI and BDA in PHC presuppose reliable digital records. Saudi evidence shows that this foundation remains incomplete. In 2018, 108 of 274 MoH PHC centres had EMR solutions and the unified digital medical record was not yet realised (MoH, 2018). Health information systems were reported in 29% of primary care centres between 2011 and 2019 (Tash & Al-Bawardy, 2023). A national mixed-methods study found implemented EHR systems in 150 of 2,259 PHC centres; among 351 practitioners, lack of training (83.8%), inadequate infrastructure and connectivity (78.5%), lack of technical support (75.5%) and lack of end-user involvement (74.6%) were the leading barriers, and interoperability was a recurring qualitative concern (Alzghaibi & Hutchings, 2025). Financial resources were positively associated with EHR implementation success (Alzghaibi et al., 2022). Data quality is the dominant worry of Saudi professionals: data management concerns scored highest (mean 3.78), led by the impact of poor data entry (mean 4.15) (Alsaedi et al., 2024). Internationally, data-leakage risk was a root factor in AI service adoption (Yang et al., 2022), and in Saudi hospitals data quality, availability, compatibility and infrastructure were technological enablers of BDA (Almoosa, 2025). Technological readiness for AI therefore depends less on algorithms than on complete, standardised and interoperable PHC data.

3.2.4 Environmental Readiness: Policy, Regulation and Ethics

The external environment in Saudi Arabia has changed quickly. The National Strategy for Data and AI names health as a priority sector (Saudi Data and Artificial Intelligence Authority [SDAIA], 2020). SDAIA's AI Ethics Principles set out seven principles, including fairness, privacy and security, transparency and explainability, and accountability, with risk-tiered obligations (SDAIA, 2023). The Personal Data Protection Law came into force in September 2023 and treats health data as sensitive data requiring explicit consent (Personal Data Protection Law, 2021/2023). The SFDA issued guidance for AI/ML-enabled medical devices in January 2023 covering quality management, risk management, clinical validation and post-market monitoring (Saudi Food and Drug Authority [SFDA], 2023), although its binding status has been questioned (Solaiman, 2024). Internationally, WHO guidance sets six principles for AI in health, from protecting autonomy to ensuring inclusiveness and sustainability (WHO, 2021a), and the Global Strategy on Digital Health has been extended to 2027 (WHO, 2021b). Explainability remains a cross-cutting requirement for clinical acceptance and legal accountability (Amann et al., 2020). The evidence suggests that Saudi Arabia's formal environment is comparatively well developed; whether PHC professionals know and trust these frameworks is less clear.

3.3 Contextual Factors: The Saudi and Al Madinah Context

National reviews describe growing but uneven AI activity. A systematic review of 13 Saudi studies identified missing AI-specific governance, insufficient capital, cultural acceptance and patient trust, skills gaps and cybersecurity as challenges (Aljehani & Al Nawees, 2025). Only 2 of 34 major Saudi hospitals had dedicated AI centres and 3 had implemented AI in patient care (Bayer & Eisawi, 2025). The digital response to COVID-19 produced around 19 apps and platforms, demonstrating capacity for rapid national deployment (Hassounah et al., 2020), and by 2023 virtual services accounted for 36% of appointments and consultations through national platforms (Health Sector Transformation Program, 2023). Evidence specific to Al Madinah is scarce. The only verified PHC study identified reports poor metabolic control in 15 centres (Alfadhli et al., 2025), and no peer-reviewed study of AI

or BDA readiness among practising PHC professionals in Al Madinah was identified in this review. Most Saudi readiness evidence is hospital-based, single-city and convenience-sampled.

Table 1: Characteristics of key empirical studies on AI/BDA value and readiness

Study	Country	Design	Population / setting	Technology	Dimension	Principal finding	Main limitation
Abràmoff et al. (2018)	USA	Prospective pivotal trial	900 people with diabetes, primary care	Autonomous DR AI	Value	Sensitivity 87.2%, specificity 90.7%	Accuracy only; sponsor-led
Ruamviboonsuk et al. (2022)	Thailand	Prospective interventional cohort	7,940 patients, 9 primary care sites	Deep-learning DR screening	Value	Sensitivity 91.4%, specificity 95.4% for vision-threatening DR	Non-randomised
Wolf et al. (2024)	USA	RCT	164 youths with diabetes	Autonomous DR AI	Value	Exam completion 100% vs 22%	Small, single system
Liu et al. (2025)	Multinational	Meta-analysis, 20 studies	EHR-based CVD prediction	ML vs risk scores	Value	AUC 0.865 (RF) vs 0.765	$I^2 > 99\%$; publication bias
Christodoulou et al. (2019)	Multinational	Systematic review, 71 studies	Clinical prediction models	ML vs logistic regression	Evidence gap	No advantage at low risk of bias	Not PHC-specific
Ghafoor et al. (2026)	Multinational	Systematic review, 36 studies	Diabetes complications	ML vs statistical models	Evidence gap	Modest gains; 8% externally validated	Heterogeneous outcomes
Plana et al. (2022)	Multinational	Systematic review, 41 RCTs	Health care	ML interventions	Evidence gap	No trial met all CONSORT-AI items	Few PHC trials
Wong et al. (2021)	USA	External validation cohort	27,697 inpatients	Proprietary sepsis model	Evidence gap	AUC 0.63; 67% of cases missed	Hospital setting
Kueper et al. (2020)	Multinational	Scoping review, 405 studies	AI and primary care	Mixed AI	Evidence gap	14.1% had a primary care author	Mapping only
Lambert et al. (2023)	Multinational	Integrative review, 42 studies	Hospital professionals	Mixed AI	Individual	Autonomy fears and workflow barriers; training facilitates	Hospitals only
Alsudairy et al. (2025)	Saudi Arabia	Cross-sectional survey	250 primary care professionals	AI tools	Individual / organisational	47.2% unfamiliar; 31.6% users; cost 49.2% top barrier	Descriptive; atheoretical
Alhazmi (2025)	Saudi Arabia	Cross-sectional survey	201 physicians	Clinical decision AI	Individual	82.1% trust vs 25.9% use	Convenience sample
Elnaggar et al. (2023)	Saudi Arabia	Cross-sectional survey	1,026 providers	AI general	Individual	73.3% expect replacement	Social-media sampling

Study	Country	Design	Population / setting	Technology	Dimension	Principal finding	Main limitation
Alsaedi et al. (2024)	Saudi Arabia	Cross-sectional survey	314 professionals	AI general	Technological	Data management top worry (mean 3.78)	Convenience strata
Waheed & Liu (2024)	Qatar	Cross-sectional survey	102 family physicians, PHC	AI general	Individual	78.4% aware; AI seen as augmenting	14.1% response
Alsalloum et al. (2026)	UAE	Survey with SEM	182 practitioners	AI general	Individual	Acceptance → readiness β = .874	Moderate model fit
Kruszyńska-Fischbach et al. (2022)	Poland	Survey with PLS-SEM	371 PHC managers	e-health	Organisational	Strategy and culture drive readiness	Not AI-specific
Alzghaibi & Hutchings (2025)	Saudi Arabia	Mixed methods	351 PHC practitioners, 14 policymakers	EHR	Technological	EHR in 150 of 2,259 PHCs; training gap 83.8%	Not AI-specific
Kumar et al. (2025b)	Saudi Arabia	Review + expert weighting	10 experts	AI literacy	TOE	Organisational weight 0.51	Very small panel
Almoosa (2025)	Saudi Arabia	Qualitative multiple-case	36 interviews, 5 hospitals	BDA	TOE	Data quality, literacy, culture as enablers	Thesis; hospitals

Note. DR = diabetic retinopathy; RF = random forest; PHC = primary health care; SEM = structural equation modelling.

Table 2: Thematic synthesis of the evidence

Theme	Consistent findings	Conflicting or uncertain evidence	Main limitations	Implications for PHC readiness
Value of AI/BDA	Image-based DR screening is accurate and improves screening uptake	ML superiority in risk prediction disappears in low-bias comparisons	Few RCTs; little Gulf evidence	Prioritise use cases with prospective evidence
Evidence-to-practice gap	External validation rare; bias and dataset shift documented	Vendor-reported vs independent performance	Mostly hospital examples	Readiness must include local validation and monitoring
Individual readiness	Positive but conditional attitudes; training improves acceptance	High replacement fear in Saudi samples vs augmentation views in Qatar	Cross-sectional, convenience samples	Training and trust-building precede adoption
Organisational readiness	Leadership, culture, resources and change management are decisive	Relative weight of organisational vs technical factors varies	Few PHC studies	Assess organisational commitment and efficacy, not only attitudes
Technological readiness	Incomplete EHR coverage and poor data quality limit analytics	Rapid platform growth vs patchy PHC records	Coverage figures are dated	Data quality and interoperability are prerequisites
Environmental readiness	Saudi regulatory and ethical frameworks now exist	Binding status and awareness among clinicians unclear	Policy analysis rather than empirical study	Translate national rules into PHC-level governance

4. Discussion

4.1 Synthesis Across Levels and Conflicting Findings

The evidence points to a layered structure of readiness. At the technical level, AI and BDA offer demonstrable value for some PHC tasks, notably retinopathy screening, but less certain value for prediction models whose apparent gains shrink under rigorous validation. At the individual level, professionals in Saudi Arabia and elsewhere tend to see AI as useful while reporting limited knowledge and low use. At the organisational and technological levels, resources, leadership, training and data infrastructure appear to determine whether favourable attitudes become use. The environmental level, which in Saudi Arabia now includes national AI strategy, ethics principles, data protection law and device regulation, sets the conditions under which organisations can act. Read together, the studies suggest that individual acceptance is necessary but not sufficient, and that organisational and data readiness are the stronger constraints in PHC. This interpretation is consistent with expert weightings in Saudi Arabia and Finland that place organisational factors first (Kumar et al., 2025b; Pulkkinen et al., 2025) and with Saudi PHC data showing that training and infrastructure gaps dominate EHR implementation barriers (Alzghaibi & Hutchings, 2025).

Three tensions stand out. First, meta-analytic advantages for ML in cardiovascular prediction (Liu et al., 2025) conflict with evidence of no advantage under low risk of bias (Christodoulou et al., 2019; Chowdhury et al., 2022). The difference is plausibly methodological: heterogeneous datasets, internal-only validation and selective reporting inflate ML performance. Second, fear of job replacement is reported by most Saudi professionals (Abdullah & Fakieh, 2020; Elnaggar et al., 2023), whereas Qatari family physicians and international nursing samples see AI as augmenting their role (Waheed & Liu, 2024; El Arab et al., 2025). Differences in question wording, sampling channels, professional mix and exposure to AI may explain this gap, as experts with prior AI project involvement rated challenges as less substantial (Pulkkinen et al., 2025). Third, high trust co-exists with low use (Alhazmi, 2025). This is consistent with TAM's weaker link to actual use (Turner et al., 2010) and with evidence that resistance to change moderates the intention–use path (Shahbaz et al., 2019). All of these studies are cross-sectional, so associations between attitudes, readiness and use cannot be interpreted causally.

4.2 Theoretical and Conceptual Implications

No single model accounts for the evidence. TAM captures individual appraisals but treats organisational conditions as external. TOE captures organisational and environmental conditions but says little about how professionals appraise a specific tool. Readiness-for-change theory adds the shared commitment and efficacy that link the two, and NASSS warns that complexity across domains can stall adoption even when each domain looks ready. An integrated TAM–TOE model, extended with trust and change readiness, is therefore justified as a working framework for PHC (Figure 1). The framework distinguishes relationships with empirical support in the reviewed literature from relationships that remain hypotheses for testing in the Al Madinah context.

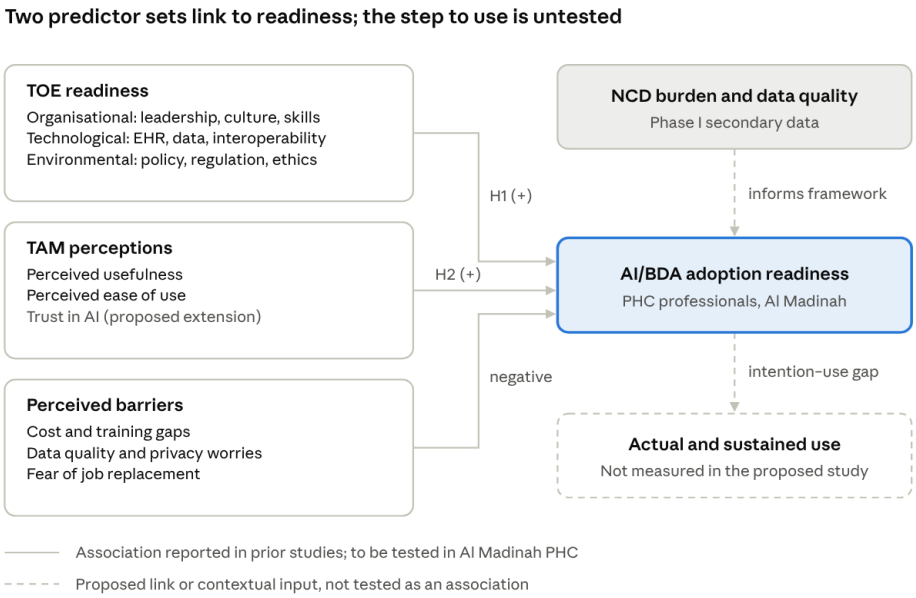


Figure 1: Conceptual framework. TOE readiness and TAM perceptions are hypothesised to be positively associated with adoption readiness and perceived barriers negatively; all three associations have support in other settings but remain untested in Al Madinah PHC. Trust is a proposed extension, and the link from readiness to sustained use is not tested by a cross-sectional design.

4.3 Implications for Policy and Practice

For health clusters, readiness assessment should precede procurement: PHC centres need baseline measures of data completeness, EHR coverage, connectivity and staff competence before predictive tools are introduced. Use cases with prospective evidence, such as AI-supported retinopathy screening, are reasonable first candidates, while risk prediction models should be locally validated against Saudi PHC data and monitored for drift and bias before routine use. Workforce strategy should combine role-specific training with clear communication that AI is intended to support rather than replace staff, given the high replacement fear in Saudi samples. Governance should translate national frameworks, including the SDAIA principles, the PDPL and SFDA guidance, into PHC-level procedures for consent, accountability and model oversight, and should address unsanctioned use of generative AI tools.

4.4 Limitations and Research Gaps

This is a narrative review. The search was not exhaustive or reproducible in the sense required of a systematic review, screening was not duplicated, and no formal risk-of-bias tool was applied, so relevant studies may have been missed and selection may reflect the authors' judgement. Several sources were checked through publisher or index records rather than full texts, and a small number of bibliographic details remain to be confirmed. Much of the Saudi evidence comes from cross-sectional surveys with convenience samples, often in single cities and hospitals, which limits generalisability to PHC in Al Madinah. Finally, AI and generative AI tools are changing rapidly, so evidence from before 2023 may understate current exposure and use.

Table 3 summarises the gaps that the evidence supports and distinguishes them from the specific contribution of the proposed study.

Table 3: Summary of research gaps

Gap	Status	Supporting evidence	Relevance to the proposed study	Potential contribution
AI/BDA readiness among practising PHC professionals in Al Madinah	Established in this review; requires systematic confirmation	No Madinah study of practising staff identified; Saudi studies mostly hospital-based (Alhazmi, 2025; Alkhatieb & Subke, 2024)	Defines the study population and setting	First regional evidence on PHC readiness
Joint measurement of TAM and TOE readiness in PHC	Established	TAM and TOE studies largely separate; organisational instruments not AI-specific (Kruszyńska-Fischbach et al., 2022; Karaca et al., 2021)	Core analytic model (H1, H2)	Tests individual and organisational predictors together
Validated AI/BDA readiness instrument for PHC staff	Possible gap; needs verification	MAIRS-MS developed with students; ORIC validated outside health care (Karaca et al., 2021; Shea et al., 2014)	Questionnaire adaptation, EFA and CFA	Psychometric evidence for an adapted PHC instrument
Intention–use gap among Saudi professionals	Established	High trust, low use (Alhazmi, 2025; Alsudairy et al., 2025)	Readiness as outcome; barriers as negative correlate	Identifies factors associated with readiness beyond attitudes
Local data readiness for analytics	Established nationally; unmeasured regionally	EHR coverage and data quality gaps (Alzghaibi & Hutchings, 2025; Alsaedi et al., 2024)	Phase I secondary data quality assessment	Describes regional data completeness and NCD burden
Context-specific, expert-validated readiness framework for PHC	Established	Existing frameworks generic or hospital-based (Alami et al., 2021; Greenhalgh et al., 2017)	Phase III Delphi	A validated framework for health-cluster planning
Prospective evidence of AI/BDA impact in Saudi PHC	Established	No Gulf RCTs reported (Martindale et al., 2024)	Outside scope; a future step	Readiness data to inform later trials

5. Conclusion

AI and BDA offer credible but uneven opportunities for chronic disease management and public health in primary care. The clearest gains concern image-based screening, while prediction models have often been overstated and seldom validated prospectively or in primary care. The literature indicates that readiness to adopt these technologies is shaped jointly by professionals' perceived usefulness and trust, by organisational leadership, culture, skills and resources, by the completeness and quality of PHC data, and by the regulatory and ethical environment. Saudi Arabia has built a strong national policy and platform base under Vision 2030, but PHC-level evidence shows

incomplete EHR coverage, data-quality concerns, limited AI knowledge and low use. Evidence from Al Madinah is particularly scarce. A theory-based assessment of AI and BDA readiness among PHC professionals in Al Madinah, combining TAM and TOE constructs with local data on disease burden and an expert-validated framework, would address a gap that this review identifies and would give health-cluster leaders an evidence base for sequencing adoption safely and equitably.

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