International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Operating Publisher
SciFormat Publishing Inc.
ISNI: 0000 0005 1449 8214

2734 17 Avenue SW,
Calgary, Alberta, T3E0A7,
Canada
+15878858911
editorial-office@sciformat.ca

ARTICLE TITLE	ARTIFICIAL INTELLIGENCE AND THE DIAGNOSTIC INVISIBILITY OF WOMEN'S METABOLIC DISORDERS: A NARRATIVE REVIEW OF SOCIO-TECHNICAL CHALLENGES IN PCOS/PMOS RECOGNITION
DOI	https://doi.org/10.31435/ijitss.2(50).2026.5908
RECEIVED	12 March 2026
ACCEPTED	08 June 2026
PUBLISHED	18 June 2026
LICENSE	The article is licensed under a **Creative Commons Attribution 4.0 International License.**

ARTIFICIAL INTELLIGENCE AND THE DIAGNOSTIC INVISIBILITY OF WOMEN'S METABOLIC DISORDERS: A NARRATIVE REVIEW OF SOCIO-TECHNICAL CHALLENGES IN PCOS/PMOS RECOGNITION

Kinga Mehal *(Corresponding Author, Email: mehalkinga@gmail.com)*
T. Marciniak Lower Silesian Specialist Hospital, Fieldorfa 2, 54-049 Wroclaw, Poland
ORCID ID: 0009-0000-5216-964X

Weronika Martyna Pielich
University Clinical Hospital in Szczecin, Unii Lubelskiej 1, 71-252 Szczecin, Poland
ORCID ID: 0009-0004-5901-0980

Natalia Siusta
University Clinical Hospital in Szczecin, Unii Lubelskiej 1, 71-252 Szczecin, Poland
ORCID ID: 0009-0000-2466-0917

Katarzyna Gałan
Lower Silesian Center of Oncology, Pulmonology, and Hematology, Plac Ludwika Hirszfelda 12, 53-413 Wroclaw, Poland
ORCID ID: 0009-0000-2349-0901

Sandra Kuczyńska
University Clinical Hospital in Bialystok, Marii Skłodowskiej-Curie 24A, 15-276 Bialystok, Poland
ORCID ID: 0009-0008-0432-3866

Natalia Balicka-Dworczak
University Clinical Hospital in Szczecin, Unii Lubelskiej 1, 71-252 Szczecin, Poland
ORCID ID: 0009-0000-9742-7454

ABSTRACT

Background: The 2026 proposal to rename Polycystic Ovary Syndrome (PCOS) as Polyendocrine Metabolic Ovarian Syndrome (PMOS) reflects a shift from an ovarian and fertility-centered paradigm toward a systemic endocrine-metabolic understanding of the disorder. Diagnostic delays in PCOS/PMOS are not only clinical but also socio-technical, shaped by fragmented care, gendered interpretation of symptoms, and electronic health record systems that privilege coded reproductive diagnoses over dispersed metabolic, dermatological, and psychological signals.
Methods: This narrative review synthesizes literature identified in PubMed and Scopus, focusing primarily on publications from 2015 to 2026 and supplemented by foundational sources on PCOS pathophysiology, clinical guidelines, artificial intelligence, explainable machine learning, electronic health records, and gender bias in healthcare.
Results: AI-supported EHR analysis may facilitate earlier recognition of PCOS/PMOS by linking structured laboratory data, ultrasound findings, and unstructured clinical narratives across specialties. Natural language processing may identify early warning signs recorded in dermatology, primary care, gynecology, and endocrinology notes, while predictive machine learning models may detect longitudinal metabolic trajectories before formal diagnosis. However, these systems may reproduce historical bias if trained on incomplete or gendered datasets.
Conclusions: AI should be understood as a socio-technical intervention rather than a purely technical diagnostic solution. Its value depends on transparency, explainability, bias-aware validation, and preservation of the patient's narrative.

KEYWORDS

Polycystic Ovary Syndrome, Polyendocrine Metabolic Ovarian Syndrome, Artificial Intelligence, Electronic Health Records, Diagnostic Delay, Gender Bias

CITATION
Kinga Mehal, Weronika Martyna Pielich, Natalia Siusta, Katarzyna Gałan, Sandra Kuczyńska, Natalia Balicka-Dworczak. (2026) Artificial Intelligence and the Diagnostic Invisibility of Women's Metabolic Disorders: A Narrative Review of Socio-Technical Challenges in PCOS/PMOS Recognition. *International Journal of Innovative Technologies in Social Science*. 2(50). doi: 10.31435/ijitss.2(50).2026.5908

1. Introduction

Polycystic Ovary Syndrome (PCOS), recently proposed to be renamed Polyendocrine Metabolic Ovarian Syndrome (PMOS), is a heterogeneous endocrine-metabolic disorder involving reproductive, metabolic, dermatological, and psychological dimensions (Azziz, 2018; Escobar-Morreale, 2018; Rosenfield & Ehrmann, 2016; Teede et al., 2026). Although historically classified through ovarian and reproductive criteria, the condition extends far beyond menstrual irregularities and fertility issues. Patients may present with acne, hirsutism, androgenetic alopecia, weight-management resistance, insulin resistance, dyslipidemia, hepatic steatosis, and increased long-term cardiometabolic risk (Barber et al., 2019; Kumarendran et al., 2018; Legro et al., 2013; Stepto et al., 2013).

Despite this systemic profile, PCOS/PMOS is frequently recognized through fragmented healthcare pathways. Patients may consult dermatologists, gynecologists, primary care physicians, dietitians, and mental health professionals before their symptoms are connected into a coherent diagnostic explanation. Diagnostic delay and lack of information are associated with dissatisfaction, psychological burden, and reduced trust in healthcare (Dokras et al., 2018; Gibson-Helm et al., 2017; Peña et al., 2022; Silva et al., 2025).

This diagnostic problem is also socio-technical. Electronic health record systems often privilege coded reproductive diagnoses while clinically relevant metabolic, dermatological, and psychological signals remain dispersed across unstructured notes. Artificial intelligence, particularly natural language processing and machine learning, may help integrate these signals and support earlier recognition of systemic disease trajectories (Rajkomar et al., 2018; Topol, 2019). At the same time, AI systems trained on historically incomplete or biased documentation may reproduce the diagnostic blind spots they are intended to correct (Cirillo et al., 2020; Obermeyer et al., 2019).

This narrative review evaluates the role of AI-supported EHR analysis in PCOS/PMOS recognition as a socio-technical problem. It asks how digital tools may support earlier identification of endocrine-metabolic patterns, how they may affect the clinician-patient relationship, and what safeguards are necessary to prevent algorithmic amplification of gendered diagnostic inequality.

2. Methodology

This article is a narrative review aimed at mapping and synthesizing literature relevant to the application of artificial intelligence in the diagnosis and recognition of PCOS/PMOS. A narrative review design was selected because the research question crosses several domains: endocrinology, women's health, digital medicine, artificial intelligence, electronic health records, patient experience, and sociology of diagnosis. The objective was not to perform a quantitative meta-analysis, but to develop an interpretive synthesis of how AI-supported diagnostic infrastructures may influence recognition of a heterogeneous endocrine-metabolic disorder.

The literature search was conducted in May 2026 using PubMed and Scopus. The search focused primarily on publications from 2015 to 2026, while older foundational sources were included when they were essential for understanding diagnostic criteria, pathophysiology, or key interpretive concepts. The search strategy combined three conceptual domains: clinical terminology, technological mechanisms, and socio-medical interpretation.

Clinical search terms included: "polycystic ovary syndrome," "PCOS," "polyendocrine metabolic ovarian syndrome," "PMOS," "insulin resistance," "hyperandrogenism," "polycystic ovarian morphology," "cardiometabolic risk," and "diagnostic delay." Technological search terms included: "artificial intelligence," "machine learning," "deep learning," "natural language processing," "clinical BERT," "electronic health records," "EHR phenotyping," "explainable artificial intelligence," "SHAP," and "LIME." Socio-medical search terms included: "gender bias," "diagnostic inequality," "women's health," "patient experience," "diagnostic odyssey," "underdiagnosis," "mental health," "body image," and "health disparities."

The literature was selected purposively rather than systematically, reflecting the interdisciplinary nature of the review. Priority was given to sources linking PCOS/PMOS diagnosis, patient experience, EHR-based AI, explainability, and healthcare bias. Publications that did not contribute to the clinical or socio-technical argument of the review were not included in the final synthesis.

The selected literature was synthesized thematically around four analytical categories: (1) the limitations of morphology-centered diagnostic logic; (2) the social and institutional production of diagnostic delay; (3) AI-supported reconstruction of diagnostic trajectories through EHR data; and (4) risks of algorithmic bias and requirements for explainable, accountable implementation.

As a narrative review based on previously published literature, this study did not involve human participants, patient-level data collection, or animal subjects. Therefore, ethics committee approval was not required.

3. PCOS/PMOS as a Clinical and Socio-Technical Problem

3.1. From reproductive reductionism to systemic recognition

The proposed transition from PCOS to PMOS is more than a terminological update. It represents an attempt to reframe the syndrome as systemic rather than primarily ovarian. By removing the anatomically misleading emphasis on "polycystic ovaries," the PMOS framework diminishes the role of pelvic ultrasound as the symbolic gatekeeper of diagnosis and highlights endocrine and metabolic dysfunction as core elements of the disease process (Teede et al., 2026). This shift is directly relevant to social science because it raises questions about whose symptoms are recognized, whose narratives are believed, and how institutional technologies either reproduce or challenge diagnostic invisibility.

Traditional diagnostic frameworks placed strong emphasis on ovarian morphology, specifically the visualization of polycystic ovarian morphology via ultrasound. This narrow focus on reproductive organs meant that patients exhibiting a predominantly metabolic, dermatological, or psychological phenotype could be misclassified or overlooked when ovarian ultrasound remained normal, when biochemical abnormalities were subtle, or when symptoms were distributed across several specialties. The term "polycystic ovary syndrome" can therefore be misleading because it places the ovary at the conceptual center of a disorder that is often metabolic, endocrine, dermatological, psychological, and social in its consequences.

3.2. Patient experience, embodiment, and diagnostic delay

The diagnostic problem is not merely biomedical. It is also sociological. Patients often cycle between dermatologists for skin lesions, dietitians or primary care physicians for unexplained weight gain, gynecologists for menstrual irregularity, and mental health professionals for anxiety, depression, or eating disturbances. Without a unified interpretive framework, no single specialist may connect these symptoms to a common endocrine-metabolic disorder. This pattern has been described as a diagnostic odyssey, in which delayed diagnosis and lack of information contribute to dissatisfaction, psychological burden, and loss of trust in care.

The psychosocial dimension of PCOS/PMOS is particularly important for a journal focused on technology and society. The syndrome affects visible, intimate, and socially meaningful aspects of embodiment, including hair growth, acne, weight, menstruation, fertility, sexuality, and body image. Qualitative research has shown that women may experience PCOS as a threat to femininity and self-understanding (Kitzinger & Willmott, 2002). More recent work examining patient satisfaction and experiences has also shown that patients may feel dismissed or not taken seriously within clinical encounters (Ismayilova & Yaya, 2022). Mental health evidence further supports this burden: PCOS is associated with increased depressive and anxiety symptoms, reduced quality of life, eating disorders, and measurable mental health-related economic costs (Cooney et al., 2017; Dokras et al., 2018; Yadav et al., 2023). These findings show that diagnosis does not only classify disease; it can validate experience, reduce uncertainty, and restore coherence to the patient's relationship with her own body.

3.3. The technological translation gap

Modern healthcare systems face a technological translation gap. Current electronic health record systems are closely tied to historical definitions, billing codes, and specialty-specific documentation practices. Hospital alert systems are usually designed to react to diagnostic codes related to infertility, amenorrhea, or gynecological findings, often ignoring text entries describing resistant acne, weight fluctuation, fatigue, mood symptoms, or early metabolic abnormalities. A typical clinician working under time pressure cannot manually search through years of unstructured medical notes from various clinics to synthesize a patient's metabolic risk profile.

Artificial intelligence, particularly natural language processing and machine learning algorithms capable of analyzing structured and unstructured EHR data, offers a conceptual method to accelerate the adoption of updated diagnostic criteria (Rajkomar et al., 2018; Topol, 2019). However, AI must not be understood as a neutral technical instrument. Computational models learn from historical datasets accumulated over decades. If those datasets reflect a narrow gynecological approach, undercoding, dismissal of women's symptoms, or incomplete documentation, AI may reproduce rather than correct the diagnostic blind spots it is intended to overcome (Cirillo et al., 2020; Obermeyer et al., 2019).

4. Results

Analysis of the selected literature reveals three major findings relevant to AI-supported PCOS/PMOS recognition. First, clinical and digital medicine literature increasingly supports a shift from isolated morphology-based assessment toward multimodal recognition of systemic disease patterns. Second, patient-experience and psychosocial studies show that diagnostic delay affects mental health, body image, trust, and the clinician-patient relationship. Third, AI-supported EHR analysis may help reconstruct dispersed diagnostic trajectories, but only if issues of bias, missing data, and explainability are explicitly addressed.

4.1. From morphology-centered PCOS to systemic PMOS

The reviewed literature demonstrates that PCOS has long been defined through overlapping reproductive, endocrine, and metabolic criteria. Classical diagnostic approaches relied on combinations of ovulatory dysfunction, clinical or biochemical hyperandrogenism, and polycystic ovarian morphology (Legro et al., 2013; Teede et al., 2018). This diagnostic flexibility allowed broader recognition of phenotypic heterogeneity, but in practice, ovarian morphology often retained disproportionate symbolic and operational importance.

Modern clinical research demonstrates that insulin resistance and compensatory hyperinsulinemia are central elements in many patients, including those maintaining a normal body mass index (Escobar-Morreale, 2018; Rosenfield & Ehrmann, 2016; Stepto et al., 2013). Excess circulating insulin acts synergistically with luteinizing hormone to stimulate ovarian theca cells, increasing ovarian androgen production. Hyperinsulinemia may also suppress hepatic synthesis of sex hormone-binding globulin, enlarging the bioavailable pool of free testosterone.

Consequently, the clinical picture extends beyond menstrual irregularities or fertility issues. Patients may present with acne, hirsutism, androgenetic alopecia, weight-management difficulty, and metabolic disturbances that increase the long-term risk of type 2 diabetes, dyslipidemia, steatotic liver disease, cardiovascular complications, and endometrial pathology (Barber et al., 2019; Haoula et al., 2012; Kumarendran et al., 2018; Legro et al., 2013). These findings support the PMOS-oriented view of the condition as a systemic endocrine-metabolic disorder rather than a primarily ovarian syndrome.

4.2. Diagnostic delay, patient experience, and mental health burden

The literature consistently shows that delayed diagnosis is not only a matter of clinical complexity but also of fragmented interpretation. Patients frequently report diagnostic delay, lack of information, and dissatisfaction with care (Gibson-Helm et al., 2017). In adolescents, diagnostic experiences may be especially sensitive because symptoms such as acne, menstrual irregularity, weight change, and hirsutism occur during a period of intense body image formation and identity development (Peña et al., 2022).

Patient-experience research strengthens this sociological interpretation. In a multi-methods study of PCOS experiences in Canada, patients described dissatisfaction with care and feeling that their symptoms were not taken seriously (Ismayilova & Yaya, 2022). Qualitative literature has also described PCOS as a condition affecting femininity, body image, sexuality, and self-understanding (Kitzinger & Willmott, 2002).

The psychological burden is substantial. PCOS is associated with depression, anxiety, reduced quality of life, and eating disorders (Cooney et al., 2017; Dokras et al., 2018). Mental health burden also has measurable economic implications, suggesting that delayed or fragmented recognition affects not only individual well-being but also healthcare systems (Yadav et al., 2023). These findings indicate that earlier and more integrated recognition may have psychosocial as well as metabolic value.

4.3. AI and the reconstruction of diagnostic trajectories

The selected literature shows an evolution in medical decision support systems from single-domain tools toward more integrated models. Earlier AI applications in gynecological endocrinology relied heavily on computer vision and deep learning systems for ultrasound image interpretation. These models were designed to automate detection, segmentation, and counting of ovarian follicles, and they may improve standardization of polycystic ovarian morphology assessment (Ghaderzadeh et al., 2025; Zhao et al., 2025).

From the perspective of PMOS, however, relying solely on imaging creates important limitations. Automated imaging systems may classify ultrasound results as normal in patients whose syndrome manifests primarily through insulin resistance, dermatological symptoms, or metabolic risk while ovarian morphology remains non-diagnostic. Therefore, AI systems limited to ultrasonographic assessment may unintentionally reinforce the morphology-centered logic that the PMOS framework seeks to overcome.

More promising are multimodal systems that integrate ultrasound findings, structured laboratory values, BMI, anti-Müllerian hormone, androgen profiles, menstrual histories, medication records, and free-text clinical notes. Machine learning models using EHR data have demonstrated potential for predicting PCOS before formal diagnosis (Zad et al., 2024). Explainable machine learning models and nomograms may further support early detection and risk stratification by showing which variables contributed to a prediction (Yao et al., 2025).

4.4. Natural language processing and the recovery of dispersed symptoms

Natural language processing is particularly relevant because many early signs of PCOS/PMOS are recorded in narrative clinical notes rather than structured fields. Complaints of fatigue, uncontrolled weight fluctuation, chronic dermatological problems, irregular cycles, distress related to body image, or repeated specialist consultations may remain invisible to systems based only on diagnostic codes and laboratory values.

Clinical language models provide a potential method for transforming narrative descriptions into computable clinical signals. Publicly available clinical BERT embeddings demonstrate the feasibility of transformer-based representation of clinical text (Alsentzer et al., 2019). In the context of PCOS/PMOS, NLP could link a dermatologist's note on resistant acne, a primary care record of weight fluctuation, a gynecological note on menstrual irregularity, and a laboratory trend suggesting insulin resistance.

This function is clinically and sociologically important. The problem is not only that relevant data are missing; it is that symptoms are often distributed across specialties and interpretive frames. Properly designed NLP systems may help reconstruct this fragmented clinical narrative, provided they preserve patient context and do not reduce lived experience to decontextualized data points.

4.5. Algorithmic bias and data quality

The promise of AI is inseparable from the risk of bias. Computational models learn from historical datasets, and historical PCOS documentation reflects decades of underdiagnosis, reproductive reductionism, inconsistent coding, and incomplete symptom capture. An algorithm trained on such data could learn to identify only patients who resemble previously diagnosed cases, while continuing to miss lean phenotypes, atypical presentations, or patients whose symptoms were dismissed or psychologized.

Sex and gender bias in biomedical AI has been recognized as a major challenge (Cirillo et al., 2020). A model trained on incomplete or biased data may perform well according to aggregate metrics while still failing clinically important subgroups. The example of racial bias in population health algorithms demonstrates that technical performance does not guarantee fairness or clinical justice (Obermeyer et al., 2019). This lesson is directly relevant to PCOS/PMOS, where formal diagnostic codes may reflect past recognition patterns rather than true disease distribution.

Missingness in EHR data is also not random. Missing laboratory values, incomplete menstrual histories, absent dermatological documentation, or lack of patient-reported distress may reflect access barriers, time pressure, clinical assumptions, or diagnostic neglect rather than absence of disease. Methods for addressing missingness in EHR-based prediction models are therefore central to safe AI development (Digitale et al., 2025). In PCOS/PMOS, missing data should be interpreted not only statistically but also institutionally: absence in the record may itself be a trace of diagnostic invisibility.

5. Implementation and Socio-Technical Implications

5.1. AI as a socio-technical intervention, not a diagnostic substitute

The publication of the 2026 PMOS consensus establishes an essential theoretical framework, shifting the focus away from reproductive parameters. However, publishing a consensus itself does not automatically change entrenched clinical workflows. Outdated algorithms embedded in digital infrastructures require restructuring to translate this physiological understanding into daily practice.

A proposed AI-driven PMOS clinical model could function as an early warning system within electronic health records (Rajkomar et al., 2018; Topol, 2019; Zad et al., 2024). Rather than waiting for a patient to explicitly report infertility, predictive architectures could continuously analyze incoming results and notes. If the algorithm detects linked events—such as androgenetic alopecia paired with increasing LDL cholesterol or repeated documentation of resistant acne and menstrual irregularity—it could generate a risk score or suggest further evaluation.

However, AI should not replace clinician judgment. It should support pattern recognition in a fragmented system. The patient's narrative must remain central, because PCOS/PMOS is experienced not as a sequence of isolated variables but as a long-term embodied disruption affecting identity, metabolism, fertility expectations, social functioning, and trust in care. A technically efficient model that reduces this experience to a probability score may improve detection while worsening relational care if implemented without explanation and dialogue.

5.2. The clinician-patient relationship and validation of symptoms

One of the most important sociological implications of AI-supported PCOS/PMOS detection concerns the clinician-patient relationship. Many patients experience delayed diagnosis as a failure of recognition. Their symptoms may be present in the record but not interpreted as connected. In such cases, AI may serve as a form of institutional memory, helping clinicians see longitudinal patterns that brief consultations obscure.

This could have a validating effect. When an AI-supported EHR system identifies a pattern across dermatology, gynecology, mental health, and metabolic records, it may help transform scattered complaints into a coherent clinical hypothesis. For the patient, this may reduce the sense of being dismissed or blamed. For the clinician, it may provide a structured prompt to ask more targeted questions and initiate earlier preventive care.

Nevertheless, validation must not be outsourced to the algorithm. If the patient is believed only when a model confirms her symptoms, the system risks replacing one form of epistemic injustice with another. The goal should be to use AI to improve clinical attention, not to make the algorithm the final authority over embodied experience.

5.3. Explainable AI and clinical accountability

Evidence-based medicine essentially rejects "black-box" diagnostic systems when they affect patient safety. This term refers to artificial intelligence models whose decision-making process remains non-transparent to the clinician, making it difficult to trace which variables or correlations led to a specific diagnostic recommendation. Explainability is therefore not an optional technical feature but a requirement for clinical accountability.

Explainable Artificial Intelligence provides interpretability for complex models. Using techniques such as SHAP or LIME, software can indicate which variables most strongly influenced a prediction (Lundberg & Lee, 2017; Ribeiro et al., 2016). When a system alerts a physician to potential PMOS risk, the interface should clearly highlight the specific phrase in the clinical narrative, laboratory trend, or cross-specialty pattern that triggered the alert. Such an architecture may provide a practical tool for early risk stratification while limiting the "black-box" effect.

However, recent literature also warns against overestimating the value of current explainability techniques in healthcare (Ghassemi et al., 2021). An explanation that is mathematically plausible may not be clinically meaningful or socially fair. Therefore, explainability should be evaluated not only by engineers but also by clinicians, patients, ethicists, and social scientists. In PCOS/PMOS, this means asking whether the model's explanation actually helps identify systemic endocrine-metabolic risk or merely reproduces visible, historically recognized features such as obesity, infertility, or ultrasound morphology.

5.4. Alert fatigue, over-medicalization, and implementation barriers

Implementing AI-supported early warning systems requires caution. In medical informatics, alert fatigue is a recognized implementation problem in which repeated or poorly targeted alerts can reduce clinician responsiveness to decision-support systems (Ancker et al., 2017). Every predictive architecture must therefore utilize adaptive sensitivity thresholds to ensure that physician alerts appear only when the probability of clinically meaningful risk is justified.

There is also a risk of over-medicalization. PCOS/PMOS exists on a spectrum of phenotypes, and not every irregular symptom cluster should be converted into a disease label without clinical assessment. AI should support careful evaluation, not automated diagnosis. This is particularly important in adolescents, lean phenotypes, and patients with overlapping conditions.

Institutional implementation also requires governance. Clinical AI tools must be validated across populations, age groups, BMI categories, and phenotypes. They must be monitored after implementation, because performance may decline when clinical documentation practices change. In PCOS/PMOS, this is especially important because renaming the condition and changing diagnostic emphasis may alter the very patterns that algorithms are expected to learn.

5.5. Lifestyle, responsibility, and stigma

In clinical practice, this syndrome is characterized by immense phenotypic diversity. Observations distinguish various developmental pathways. In patients with a normal baseline body weight, neuroendocrine dysregulation may be accompanied by metabolic disturbances. Conversely, in another group, adiposity may amplify the full expression of the syndrome. Insulin resistance is a pathophysiological state, not an independent disease entity, and in many patients it is influenced by lifestyle, genetic predisposition, adiposity, inflammation, and endocrine factors.

Integrating AI diagnostics introduces an educational challenge. Algorithmic identification of endocrine-metabolic disorders can alleviate patient guilt and validate physical difficulties, but it should not serve as an excuse for therapeutic passivity. Such diagnosis should be integrated with patient-centered strategies supporting habit change. Although technology can objectively identify biochemical barriers, effective management still relies primarily on lifestyle modification, individualized counseling, and appropriate pharmacological or reproductive management when indicated (Teede et al., 2018; Teede et al., 2023).

At the same time, lifestyle counseling must avoid moralizing blame. Weight-centered communication may reinforce stigma and discourage engagement with care. The social value of the PMOS framework lies in recognizing that metabolic risk is real while avoiding simplistic narratives that reduce the patient's condition to personal failure.

The practical difference between legacy diagnostic logic and the proposed AI-supported PMOS approach is summarized in Table 1. In the table, EHR refers to electronic health records, ICD to the International Classification of Diseases, and NLP to natural language processing. The table is not intended as a validated clinical algorithm. It is a conceptual synthesis showing how a socio-technical redesign of EHR systems could shift recognition from isolated reproductive criteria toward integrated endocrine-metabolic and patient-centered trajectories.

Table 1. Conceptual comparison of legacy PCOS-oriented EHR logic with the proposed AI-supported PMOS architecture

Diagnostic domain	Legacy PCOS strategy: current ICD-based logic	Proposed PMOS strategy: AI-augmented framework	Potential clinical and social value
System entry point	Reactive: often triggered by infertility or menstrual irregularity codes.	Proactive: triggered by cross-domain metabolic, dermatological, menstrual, psychological, and narrative signals.	May encourage earlier intervention before primary gynecological complaints or advanced complications arise.
Ultrasound utility	Primary gatekeeper: high reliance on morphological ovarian criteria.	Ancillary metric: integrated alongside systemic biochemical and narrative profiles.	May reduce diagnostic exclusion of patients with primarily metabolic phenotypes and normal ultrasound results.
Data synthesis	Static: point-in-time analysis of structured laboratory values.	Longitudinal: multimodal analysis of clinical narratives and temporal trends.	Aims to extract systemic markers hidden in unstructured physician notes.
Patient narrative	Often fragmented across specialties and reduced to isolated symptoms.	Reconstructed across EHR domains using NLP-supported semantic linkage.	May support validation of patient experience and improve clinician-patient communication.
Risk of bias	Historical underdiagnosis remains embedded in codes and workflows.	Bias-aware model development and explainable outputs required.	May reduce or reproduce inequality depending on data quality and governance.
Clinical focus	Symptomatic management of localized anatomical or reproductive issues.	Preventive recognition of endocrine-metabolic risk and cardiovascular trajectory.	May lower the long-term burden of metabolic complications.

Note. EHR = electronic health records; ICD = International Classification of Diseases; NLP = natural language processing.

As Table 1 indicates, the central issue is not whether AI can simply "detect PCOS" with higher accuracy. The more important question is whether AI can help healthcare systems recognize dispersed symptoms earlier without reproducing the same social and clinical filters that historically made many patients invisible. The value of AI therefore depends on its integration into accountable clinical workflows, not on algorithmic performance alone.

6. Discussion

This narrative review shows that PCOS/PMOS recognition cannot be reduced to the technical accuracy of diagnostic tools. The central finding is that delayed diagnosis emerges from the interaction between clinical heterogeneity, fragmented care, gendered symptom interpretation, and digital infrastructures built around historically narrow diagnostic categories. AI-supported EHR analysis may therefore be valuable not simply because it can improve prediction, but because it may help reconstruct dispersed clinical trajectories that are currently difficult for individual clinicians to synthesize during brief consultations.

The significance of this finding lies in reframing AI as a socio-technical instrument. In PCOS/PMOS, the relevant question is not only whether machine learning can detect disease earlier, but whether it can support more equitable recognition of patient experience. Natural language processing and predictive analytics may help identify patterns across dermatology, gynecology, primary care, endocrinology, and mental health records. However, these benefits depend on careful validation, explainability, and awareness of historical bias in clinical documentation.

For the field of digital health, PCOS/PMOS offers an instructive case of how AI may either reduce or reinforce diagnostic inequality. If algorithms are trained on incomplete or biased records, they may reproduce the same under-recognition that affected previous generations of patients. If designed responsibly, they may support earlier preventive care, improve clinician-patient communication, and strengthen women's cardiometabolic health. Future research should therefore examine not only predictive performance, but also patient trust, clinical workflow integration, bias monitoring, and the social consequences of AI-supported diagnosis.

7. Conclusions

The recent proposal to redefine PCOS as Polyendocrine Metabolic Ovarian Syndrome emphasizes the serious metabolic complications inscribed in this disorder, moving away from the historical reduction of the problem solely to reproductive or ovarian issues. For this clinical knowledge to translate into better patient outcomes, healthcare systems must evolve beyond outdated software based on narrow diagnostic codes and fragmented specialty documentation.

The future of comprehensive ambulatory care may rely on implementing natural language processing algorithms capable of extracting early warning signs from unstructured clinical interviews, combined with machine learning models that learn from biochemical fluctuations and longitudinal trajectories. Implemented through transparent Explainable Artificial Intelligence architectures, these tools have the potential to relieve staff, shorten the diagnostic odyssey, and support earlier preventive strategies.

However, AI should not be understood as a neutral technological cure for diagnostic delay. It is a socio-technical intervention whose effects depend on data quality, explainability, governance, clinician training, and attention to patient experience. In PCOS/PMOS, the central challenge is not only detecting disease earlier but also correcting a historical pattern in which women's symptoms have been fragmented, psychologized, or interpreted too narrowly through reproductive criteria.

Digital innovations should support clinicians in the early initiation of preventive strategies, reinforcing the fundamental role of lifestyle modification in women's cardiometabolic health. Ultimately, they may help end years of patients wandering between multiple specialists' offices, restoring the chance for early, adequate treatment and a fuller understanding of the nature of their illness and body.

Ethics approval: Not required. This narrative review is based exclusively on previously published literature and does not involve direct recruitment of human participants, patient-level data collection, or animal experimentation.

Informed consent: Not applicable. No primary patient data or individual clinical cases were collected for the purpose of this review.

Conflict of interest: No conflicts of interest to declare.

Funding: This research received no external funding.

REFERENCES

1. Alsentzer, E., Murphy, J. R., Boag, W., Weng, W. H., Jin, D., Naumann, T., & McDermott, M. (2019). Publicly available clinical BERT embeddings. In *Proceedings of the 2nd Clinical Natural Language Processing Workshop* (pp. 72–78). https://doi.org/10.18653/v1/W19-1909
2. Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making, 20*, Article 310. https://doi.org/10.1186/s12911-020-01332-6
3. Ancker, J. S., Edwards, A., Nosal, S., Hauser, D., Mauer, E., Kaushal, R., & HITEC Investigators. (2017). Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system. *BMC Medical Informatics and Decision Making, 17*, Article 36. https://doi.org/10.1186/s12911-017-0430-8
4. Azziz, R. (2018). Polycystic ovary syndrome. *Obstetrics & Gynecology, 132*(2), 321–336. https://doi.org/10.1097/AOG.0000000000002698
5. Barber, T. M., Hanson, P., Weickert, M. O., & Franks, S. (2019). Obesity and polycystic ovary syndrome: Implications for pathogenesis and novel management strategies. *Clinical Medicine Insights: Reproductive Health, 13*, Article 1179558119874042. https://doi.org/10.1177/1179558119874042
6. Bozdag, G., Mumusoglu, S., Zengin, D., Karabulut, E., & Yildiz, B. O. (2016). The prevalence and phenotypic features of polycystic ovary syndrome: A systematic review and meta-analysis. *Human Reproduction, 31*(12), 2841–2855. https://doi.org/10.1093/humrep/dew218
7. Cirillo, D., Catuara-Solarz, S., Morey, C., Guney, E., Subirats, L., Mellino, S., Gigante, A., Valencia, A., Rementeria, M. J., Chadha, A. S., & Mavridis, N. (2020). Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare. *npj Digital Medicine, 3*, Article 81. https://doi.org/10.1038/s41746-020-0288-5
8. Cooney, L. G., Lee, I., Sammel, M. D., & Dokras, A. (2017). High prevalence of moderate and severe depressive and anxiety symptoms in polycystic ovary syndrome: A systematic review and meta-analysis. *Human Reproduction, 32*(5), 1075–1091. https://doi.org/10.1093/humrep/dex044
9. Digitale, J., Franzon, D., Pletcher, M. J., McCulloch, C. E., & Gennatas, E. D. (2025). Methods for addressing missingness in electronic health record data for clinical prediction models: Comparative evaluation. *JMIR Medical Informatics, 13*, Article e79307. https://doi.org/10.2196/79307

10. Dokras, A., Stener-Victorin, E., Yildiz, B. O., Li, R., Ottey, S., Shah, D., Epperson, N., & Teede, H. (2018). Androgen Excess–Polycystic Ovary Syndrome Society position statement on depression, anxiety, quality of life, and eating disorders in polycystic ovary syndrome. *Fertility and Sterility, 109*(5), 888–899. https://doi.org/10.1016/j.fertnstert.2018.01.038
11. Escobar-Morreale, H. F. (2018). Polycystic ovary syndrome: Definition, aetiology, diagnosis and treatment. *Nature Reviews Endocrinology, 14*(5), 270–284. https://doi.org/10.1038/nrendo.2018.24
12. Ghaderzadeh, M., Garavand, A., & Salehnasab, C. (2025). Artificial intelligence in polycystic ovary syndrome: A systematic review of diagnostic and predictive applications. *BMC Medical Informatics and Decision Making, 25*, Article 427. https://doi.org/10.1186/s12911-025-03255-6
13. Ghassemi, M., Oakden-Rayner, L., & Beam, A. L. (2021). The false hope of current approaches to explainable artificial intelligence in health care. *The Lancet Digital Health, 3*(11), e745–e750. https://doi.org/10.1016/S2589-7500(21)00208-9
14. Gibson-Helm, M., Teede, H., Dunaif, A., & Dokras, A. (2017). Delayed diagnosis and a lack of information associated with dissatisfaction in women with polycystic ovary syndrome. *The Journal of Clinical Endocrinology & Metabolism, 102*(2), 604–612. https://doi.org/10.1210/jc.2016-2963
15. González, F. (2012). Inflammation in polycystic ovary syndrome: Underpinning of insulin resistance and ovarian dysfunction. *Steroids, 77*(4), 300–305. https://doi.org/10.1016/j.steroids.2011.12.003
16. Haoula, Z., Salman, M., & Atiomo, W. (2012). Evaluating the association between endometrial cancer and polycystic ovary syndrome. *Human Reproduction, 27*(5), 1327–1331. https://doi.org/10.1093/humrep/des042
17. Ismayilova, M., & Yaya, S. (2022). "I felt like she didn't take me seriously": A multi-methods study examining patient satisfaction and experiences with polycystic ovary syndrome (PCOS) in Canada. *BMC Women's Health, 22*, Article 47. https://doi.org/10.1186/s12905-022-01630-3
18. Kitzinger, C., & Willmott, J. (2002). "The thief of womanhood": Women's experience of polycystic ovarian syndrome. *Social Science & Medicine, 54*(3), 349–361. https://doi.org/10.1016/S0277-9536(01)00034-X
19. Kumarendran, B., O'Reilly, M. W., Manolopoulos, K. N., Toulis, K. A., Gokhale, K. M., Sitch, A. J., Wijeyaratne, C. N., Coomarasamy, A., Arlt, W., & Nirantharakumar, K. (2018). Polycystic ovary syndrome, androgen excess, and the risk of nonalcoholic fatty liver disease in women: A longitudinal study based on a United Kingdom primary care database. *PLOS Medicine, 15*(3), Article e1002542. https://doi.org/10.1371/journal.pmed.1002542
20. Legro, R. S., Arslanian, S. A., Ehrmann, D. A., Hoeger, K. M., Murad, M. H., Pasquali, R., & Welt, C. K. (2013). Diagnosis and treatment of polycystic ovary syndrome: An Endocrine Society clinical practice guideline. *The Journal of Clinical Endocrinology & Metabolism, 98*(12), 4565–4592. https://doi.org/10.1210/jc.2013-2350
21. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems 30* (pp. 4765–4774). https://doi.org/10.48550/arXiv.1705.07874
22. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science, 366*(6464), 447–453. https://doi.org/10.1126/science.aax2342
23. Peña, A. S., Teede, H., Hewawasam, E., Hull, M. L., & Gibson-Helm, M. (2022). Diagnosis experiences of adolescents with polycystic ovary syndrome: Cross-sectional study. *Clinical Endocrinology, 96*(1), 62–69. https://doi.org/10.1111/cen.14604
24. Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G. E., Irvine, J., Le, Q., Litsch, K., ... Dean, J. (2018). Scalable and accurate deep learning with electronic health records. *npj Digital Medicine, 1*, Article 18. https://doi.org/10.1038/s41746-018-0029-1
25. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939778
26. Rosenfield, R. L., & Ehrmann, D. A. (2016). The pathogenesis of polycystic ovary syndrome (PCOS): The hypothesis of PCOS as functional ovarian hyperandrogenism revisited. *Endocrine Reviews, 37*(5), 467–520. https://doi.org/10.1210/er.2015-1104
27. Silva, E. L., Lane, K. J., Cheng, J. J., Popp, Z., van Loenen, B. D., Coull, B., Hart, J. E., James-Todd, T., & Mahalingaiah, S. (2025). Polycystic ovary syndrome underdiagnosis patterns by individual-level and spatial social vulnerability measures. *The Journal of Clinical Endocrinology & Metabolism, 110*(6), 1657–1666. https://doi.org/10.1210/clinem/dgae705
28. Stepto, N. K., Cassar, S., Joham, A. E., Hutchison, S. K., Harrison, C. L., Goldstein, R. F., & Teede, H. J. (2013). Women with polycystic ovary syndrome have intrinsic insulin resistance on euglycaemic-hyperinsulinaemic clamp. *Human Reproduction, 28*(3), 777–784. https://doi.org/10.1093/humrep/des463
29. Teede, H. J., Khomami, M. B., Morman, R., Laven, J. S. E., Joham, A. E., Costello, M. F., Patil, M., Rees, D. A., Berry, L., Cree, M. G., Zhao, H., Norman, R. J., Dokras, A., & Piltonen, T. (2026). Polyendocrine metabolic ovarian syndrome, the new name for polycystic ovary syndrome: A multistep global consensus process. *The Lancet*. Advance online publication. https://doi.org/10.1016/S0140-6736(26)00717-8

30. Teede, H. J., Misso, M. L., Costello, M. F., Dokras, A., Laven, J., Moran, L., Piltonen, T., Norman, R. J., & International PCOS Network. (2018). Recommendations from the international evidence-based guideline for the assessment and management of polycystic ovary syndrome. *Fertility and Sterility, 110*(3), 364–379. https://doi.org/10.1016/j.fertnstert.2018.05.004
31. Teede, H. J., Tay, C. T., Laven, J., Dokras, A., Moran, L. J., Piltonen, T. T., Costello, M. F., Boivin, J., Redman, L. M., Boyle, J. A., Norman, R. J., Mousa, A., Joham, A. E., & International PCOS Network. (2023). Recommendations from the 2023 international evidence-based guideline for the assessment and management of polycystic ovary syndrome. *Fertility and Sterility, 120*(4), 767–793. https://doi.org/10.1016/j.fertnstert.2023.07.025
32. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7
33. Yadav, S., Delau, O., Bonner, A. J., Markovic, D., Patterson, W., Ottey, S., Buyalos, R. P., & Azziz, R. (2023). Direct economic burden of mental health disorders associated with polycystic ovary syndrome: Systematic review and meta-analysis. *eLife, 12*, Article e85338. https://doi.org/10.7554/eLife.85338
34. Yao, B., Yu, X., Zhang, Y., Chen, J., Zhu, X., Zhang, C., & Tong, J. (2025). Development and validation of an explainable machine learning and nomogram model for early detection and risk stratification of polycystic ovary syndrome: A multicenter study. *Frontiers in Endocrinology, 16*, Article 1719631. https://doi.org/10.3389/fendo.2025.1719631
35. Zad, Z., Jiang, V. S., Wolf, A. T., Wang, T., Cheng, J. J., Paschalidis, I. C., & Mahalingaiah, S. (2024). Predicting polycystic ovary syndrome with machine learning algorithms from electronic health records. *Frontiers in Endocrinology, 15*, Article 1298628. https://doi.org/10.3389/fendo.2024.1298628
36. Zhao, B., Wen, L., Huang, Y., Fu, Y., Zhou, S., Liu, J., Liu, M., & Li, Y. (2025). A deep learning-based automatic recognition model for polycystic ovary ultrasound images. *Balkan Medical Journal, 42*(5), 419–428. https://doi.org/10.4274/balkanmedj.galenos.2025.2025-5-114