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EMERGING DIGITAL TECHNOLOGIES IN MONITORING ENDOCRINE DISORDERS: CONTINUOUS GLUCOSE MONITORING SYSTEMS AND ARTIFICIAL INTELLIGENCE IN THE DIAGNOSIS OF POLYCYSTIC OVARY SYNDROME

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ABSTRACT

Introduction and objective: Endocrine disorders affect the regulation of metabolic processes and are often associated with disturbances in glucose and hormonal homeostasis.
In recent years, digital tools have increasingly contributed to the diagnosis and monitoring of metabolic diseases. Technological advancements have introduced continuous glucose monitoring (CGM) for patients with diabetes, as well as artificial intelligence (AI) algorithms to support the assessment of hormonal and imaging parameters in the diagnosis of PCOS. Despite these advances, studies on patients with diabetes using CGM who are simultaneously diagnosed with PCOS remain limited. AI-based diagnostic tools show promising accuracy in detecting PCOS characteristics through hormonal profiles and ultrasound imaging.
The aim of this review is to summarize current evidence on CGM systems and AI in the evaluation and diagnosis of endocrine disorders, focusing on diabetes and PCOS.
Methods: This narrative review analyzed literature from 2019–2025 and one earlier publication using PubMed and Google Scholar, focusing on CGM, AI, and diagnostic approaches in endocrine disorders.
Results: CGM provides valuable insight into glucose variability and metabolic patterns in diabetes, but evidence for its use in patients with concurrent PCOS is limited. AI-based tools demonstrate high accuracy in identifying PCOS features, especially through hormonal profiling and ultrasound analysis.
Conclusion: Digital technologies such as CGM and AI offer promising opportunities to improve the evaluation and management of endocrine disorders, particularly in women with PCOS. Larger, standardized studies are needed to validate clinical utility and support integration into routine care.

KEYWORDS

Endocrine Disorders, Diabetes, Polycystic Ovary Syndrome (PCOS), Continuous Glucose Monitoring (CGM), Artificial Intelligence (AI), Metabolic Health

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1. Introduction:

Endocrine disorders are fundamentally connected to disruptions in metabolic processes. Endocrine conditions often result from the interplay of multiple metabolic dysfunctions [1].

This pattern is particularly evident in diabetes and polycystic ovary syndrome (PCOS).

These conditions are among the most significant endocrine disorders worldwide [2-5].

When examining global statistics, approximately 10% of women of reproductive age are affected by PCOS, which is characterized by hyperandrogenism, polycystic ovarian morphology, and ovulatory dysfunction. Importantly, insulin resistance and compensatory hyperinsulinemia frequently accompany PCOS, contributing to both reproductive and metabolic complications [1-3]. Similarly, diabetes mellitus, with its burden of micro- and macrovascular complications, highlights the imperative for early and accurate monitoring of metabolic health. According to the IDF Diabetes Atlas 11th Edition (2025), approximately 589 million adults aged 20–79 are living with diabetes worldwide [4,5].

The use of modern digital tools in medicine is advancing rapidly and is anticipated to become an essential element of routine clinical practice in the near future[6-8]. Continuous glucose monitoring (CGM) has been widely adopted in diabetes management. CGM delivers real-time, dynamic information on glucose fluctuations, providing a more detailed understanding of metabolic patterns than conventional single-point measurements [9,10]. However, studies on patients using CGM for diabetes who are also diagnosed with PCOS remain limited, restricting robust evaluation of AI-driven diagnostics and digital health solutions. As a result, the integration of AI into routine endocrine diagnostics is still in its early stages, highlighting the need for further investigation of its real-world effectiveness [6-8,11].

The aim of this review is to summarize current evidence on the use of continuous glucose monitoring systems and artificial intelligence in the evaluation and diagnosis of endocrine disorders, with particular emphasis on patients with diabetes and women affected by PCOS.

This review also maps the current state of knowledge and identifies gaps in implementation to guide future research and facilitate clinical translation of digital endocrine monitoring, highlighting the growing importance of evaluating emerging digital tools in improving diagnostic accuracy and metabolic assessment, given the rising prevalence of diabetes and PCOS.

2. Methodology:

A comprehensive literature search was conducted using the electronic databases PubMedand Google Scholar, covering publications from 2019 to 2025 and one publication in 2011. The search incorporated both free-text terms and combinations(and, or), including: "endocrine disorders", "diabetes", "polycystic ovary syndrome", "PCOS", "continuous glucose monitoring", "CGM", "artificial intelligence", "AI", "metabolic health", "digital health", "metabolic assessment", "diagnostic tools". Boolean operators were applied to refine and expand the search where appropriate. The search was restricted to peer-reviewed studies available in English. In addition, a manual screening of reference lists from the included studies was performed to identify any relevant publications that were not captured through database searches.

2.1. Eligibility Criteria

To ensure relevance and scientific quality, the following inclusion criteria were applied:

- peer-reviewed original research articles or review papers published in English;
- studies evaluating continuous glucose monitoring (CGM), AI-based diagnostic systems, or other digital tools relevant to endocrine or metabolic disorders;
- research involving populations with diabetes, polycystic ovary syndrome (PCOS), or other endocrine dysfunctions.

2.2. Study Selection Process

All identified records were screened in a two-step process. Initially, titles and abstracts were assessed for relevance, followed by a full-text review of potentially eligible articles. Screening was conducted independently by five reviewers, with any disagreements resolved through discussion and consensus.

2.3. Data Extraction and Analysis

For each included study, the following data were extracted: study design, population characteristics, sample size, methodology, type of digital technology used (CGM or AI), primary diagnostic or clinical outcomes, and key findings. Due to the methodological variability across studies, a narrative synthesis was performed rather than a meta-analysis. Extracted data were grouped thematically into three domains:

- applications of CGM in metabolic and endocrine assessment;
- AI-based diagnostic tools in diabetes and PCOS;
- implementation challenges and future clinical potential of digital endocrine monitoring.

3. Emerging Technologies in Endocrinology

3.1. Digital transformation in endocrinology

The rapid advancements in digital technologies have significantly transformed overall health care, primarily enabling more precise monitoring, timely interventions, and personalized diagnostics [12]. Mobile health applications, telemedicine platforms, and portable monitoring devices have become important and integral components of patient care, especially for chronic metabolic disorders. Continuous glucose monitoring (CGM), smart insulin pens, and AI-based decision support tools now allow clinicians to track physiological data in real time and, equally important, help tailor therapy to the individual needs of each patient [12-14].

3.2. Patient education and self-management

Digital health tools facilitate remote monitoring and also enable patients to actively engage in their own healthcare. Educational applications and digital systems enhance adherence to therapeutic recommendations, support healthy lifestyle modifications, and assist in the early detection of complications [14,15]. Through specially designed algorithms, they help motivate individuals to improve their well-being and health. Patient engagement via technology has been shown to improve glycemic control in diabetes and facilitate the management of symptoms in conditions such as polycystic ovary syndrome (PCOS) [16,17].

3.3. Overview of endocrine disorders requiring monitoring

Endocrine disorders such as diabetes, insulin resistance, and PCOS share a common metabolic background, including hyperinsulinemia, dysregulation of glucose metabolism and, hormonal imbalances [18]. Effective monitoring of these conditions is crucial for preventing both reproductive and metabolic complications. Continuous glucose monitoring (CGM) and AI-based diagnostic tools facilitate the early identification of abnormalities in glucose and hormonal profiles, creating opportunities for proactive, preventive interventions [13, 14, 19].

3.4. Diagnostic and therapeutic challenges

Despite rapid technological advancements, the integration of digital tools into routine clinical practice still faces several challenges. These limitations include inconsistent device accuracy, the complexity of data interpretation, patient adherence to recommendations, as well as legal and privacy concerns [20]. Moreover, many endocrine disorders follow diverse courses, highlighting the need for tailored care that combines digital tools with clinical insight [21]. Overcoming these challenges is vital for the successful integration and impact of emerging technologies in endocrinology.

4. Continuous Glucose Monitoring (CGM) Systems

4.1. Principles of CGM operation

Continuous glucose monitoring (CGM) systems rely primarily on a subcutaneous sensor that measures interstitial glucose levels at regular intervals. The sensor typically records glucose every few minutes and then transmits the data to a receiver or smartphone application for real-time analysis. These sensors generally use enzymatic reactions, most commonly glucose oxidase, to generate an electrical signal proportional to interstitial glucose concentration, which is subsequently converted into glucose values through algorithmic processing [22]. CGM devices provide detailed, and importantly, continuous glucose readings, alerts for hypo- and hyperglycemia, and data-sharing capabilities, making them minimally invasive and highly effective monitoring tools [22, 23].

4.2. Types of CGM Systems

Continuous Glucose Monitoring (CGM) systems are not homogeneous, because different devices rely on distinct principles of data acquisition, which have both clinical and practical implications. In the literature, two main categories are distinguished: real-time CGM (rtCGM) and intermittently scanned CGM (isCGM). rtCGM systems provide continuous data streaming, with the sensor transmitting glucose values to a receiver or application every few minutes. Advantages include automatic alerts for hypoglycemia and hyperglycemia, trend arrows indicating the rate and direction of glucose changes, and the possibility of immediate response. In contrast, isCGM systems require active scanning of the sensor by the user (for example, with a reader or smartphone) to obtain current glucose values. The most commonly cited example is the FreeStyle Libre system (various generations: Libre 1, Libre 2, and Libre 3). In earlier generations, the absence of automatic alerts limited functionality during rapid glucose excursions. In newer versions, alerts can be added, which brings the functionality closer to that of rtCGM; however the user still needs to scan the sensor to read glucose values [24,25].

Compared with isCGM, rtCGM in randomized controlled trials was associated with a mean increase in Time in Range (TIR) of +7.0% and a reduction in time below range (hypoglycemia) by 1.7% [26].In real-world cohort data, rtCGM use was linked to greater long-term HbA1c reduction and decreased glycemic variability (CV) compared to isCGM [25].

In summary, rtCGM offers continuous glucose data, automated alerts, and enhanced real-time responsiveness. isCGM, by contrast, provides on-demand readings, is more convenient and cost-effective, but relies on user engagement and yields less dynamic information. Overall, evidence supports the superior accuracy and stability of rtCGM, whereas isCGM may suffice for general monitoring but has inherent limitations [24-26].

4.3. Clinical applications in endocrinology

CGM was originally developed for individuals with diabetes; however, its clinical applications are increasingly expanding to other metabolic conditions [27]. In non–insulin-treated type 2 diabetes and prediabetes**, research indicates that**the use of CGM combined with mobile applications improves outcomes, including increased time in range (TIR) and better glycemic regulation [28]. In non–insulin-dependent type 2 diabetes, CGM has also been proposed as a biofeedback tool, in combination with dietary guidance, to help guide individualized treatment decisions [29]. Additionally, there is growing interest in applying CGM in individuals with prediabetes to detect dysglycemia earlier and enable timelier intervention [30].

4.4. Sensor physiology and "lag time" in CGM

CGM systems measure glucose in the interstitial fluid (ISF) rather than directly in blood plasma. In healthy adults under fasting conditions, the physiological time lag, the time needed for glucose to diffuse from the vascular compartment to the interstitial space, has been measured to be around 5–6 minutes[31]. In real-life use, the total lag (physiological plus sensor/processing delay) between plasma glucose and CGM-reported glucose values is often reported in the range, of 5 to 15 minutes, depending on the type of CGM system, the rate of glucose change, and sensor calibration/processing algorithms**.** Importantly, when glucose levels change rapidly, for instance after a meal, during insulin administration, or during physical activity, this lag may be more pronounced, which may result in the CGM underestimating or delaying detection of rapid glycemic excursions (hyperglycemia or hypoglycemia) [31,32]. Because of this lag, CGM glucose readings should be interpreted with caution, especially in situations of rapid glucose fluctuations. Calibration of CGM devices (when required) should preferably be done during periods of stable glucose levels to minimize error induced by lag and sensor filtering [33].

4.5. CGM metrics

Modern continuous glucose monitoring (CGM) systems enable not only frequent glucose measurements but also the calculation of a set of standardized metrics that provide a much richer picture of glycemic control than typical point-in-time measurements or HbA1c alone. Core CGM-derived metrics include: Time in Range (TIR)**,** Time Below Range (TBR)**,** Time Above Range (TAR)**,** glycemic variability (Coefficient of Variation, CV)**,** mean glucose**,** and Glucose Management Indicator (GMI)**.**CGM-derived metrics such as Time in Range (TIR), Time Below Range (TBR), Time Above Range (TAR), Coefficient of Variation (CV), and Glucose Management Indicator (GMI) are important because they provide adynamic and comprehensive view of glycemic control**.** Unlike single-point measurements or HbA1c, these metrics capturedaily fluctuations, risk of hypo- and hyperglycemia, and glucose variability**,** allowing clinicians topersonalize therapy, optimize safety, and evaluate treatment effectiveness more accurately [34].

4.6. Emerging evidence for CGM in PCOS

Preliminary pilot studies conducted in women with polycystic ovary syndrome (PCOS) suggest that CGM may reveal distinct patterns of glucose variability. In one study, 36 women with PCOS were monitored for 14 days using the Freestyle Libre device. It was found that individuals with insulin resistance exhibited lower glucose coefficient of variation (CV) compared to those without insulin resistance [11].

In a pilot study of pregnant women with PCOS, CGM use revealed early gestational hyperglycemia, reflected by an increased Area Under the Curve (AUC) during the OGTT, although no significant differences in CGM-derived metrics were observed. This suggests CGM may have potential for early preventive intervention, but further research is needed [35].

4.7. Limitations and Challenges of CGM Use

Despite the many advantages of CGM, a number of important limitations and constraints remain, both at the level of sensor technology and in practical, patient- or system-related aspects. **Interference by certain substances:** common medications or supplements, for example acetaminophen (paracetamol), vitamin C (ascorbic acid), and salicylates may interfere with sensor accuracy in some CGM systems, potentially leading to falsely elevated or reduced glucose readings [36].

Several studies report that CGM may undervalue or lag behind actual blood glucose, especially after meals or during rapid glycemic excursions. For example, in a comparison of CGM sensor vs capillary glucose after a standardized glucose load, CGM showed a delayed and attenuated rise in glucose in the first 45–60 minutes [37].In critically ill patients (for example after cardiac surgery), CGM has shown relatively low accuracy with mean absolute relative difference (MARD) up to 21.5% when compared to arterial blood glucose [38].

In a large study including patients with type 2 diabetes, CGM often underestimated nocturnal glucose values; comorbidities associated with diabetes further impaired CGM accuracy [39]. Because of these measurement and sensor-based limitations, CGM readings must be interpreted with caution, especially when precise glucose values are critical (such as hypoglycemia risk, insulin dosing, and perioperative care).

4.8. Educational aspects

In addition to its significant diagnostic value, CGM also functions as an educational and behavioral tool. Real-time glucose feedback enables patients to observe how lifestyle factors, such as diet, physical activity, and sleep, influence their glucose levels, allowing them to make more informed decisions. Importantly, this can motivate behavior change, enhance self-management, and support personalized lifestyle interventions. The ability of CGM to visualize glucose trends can therefore serve as a coaching tool for metabolic health. Nevertheless, it is worth emphasizing that further studies on larger populations are needed [40-42].

5. PCOS and the Role of Artificial Intelligence in Diagnosis

Polycystic Ovary Syndrome (PCOS) is the most common endocrinopathy in women of reproductive age and is significantly underdiagnosed [43]. Diagnosis of PCOS in adults is based on the modified Rotterdam criteria, which requires the presence of at least two of the following three features: clinical or biochemical signs of hyperandrogenism, irregular or absent ovulation, and polycystic ovarian morphology on ultrasound (PCOM) or elevated anti-Müllerian hormone (AMH) levels [44]. However, because of its varied manifestation and symptomatic comorbidity with other illnesses, PCOS is often underdiagnosed or misunderstood. Traditional diagnostic methods can take a long time and require the expertise of skilled specialists [45].To effectively manage PCOS and prevent potential metabolic complications such as obesity, insulin resistance, type 2 diabetes, dyslipidemia, and hypertension, early and accurate diagnosis is essential.

Artificial intelligence (AI) and machine learning (ML) are new technologies that could help doctors diagnose PCOS faster and more accurately, making clinical practice more reliable and consistent [55]. AI is the field of computer science that creates systems with human-like intelligence. ML is a branch of AI that focuses on learning from past events and using that knowledge to make decisions in the future. AI has become an increasingly valuable tool in the diagnosis of polycystic ovary syndrome (PCOS), particularly through the analysis of ultrasound imaging and clinical data. In ultrasound-based diagnosis, AI algorithms can preprocess ovarian images, segment follicles, and extract morphological and texture-related features that are relevant for identifying polycystic ovarian morphology. Machine learning algorithms then classify the images and calculate the probability of PCOS [44,46].

Previous studies analyzed clinical and biochemical parameters, including hormone levels, cycle length, anthropometric parameters, and symptoms associated with PCOS, to include these factors in AI models that can accurately find PCOS [47,48].

Another recent work combined ultrasound images with clinical and biochemical data using a machine learning algorithm [49,50]. In addition, a study developed a prediction model for PCOS based on tongue and pulse data using machine learning techniques [51].

AI offers several important benefits in both recognizing and managing PCOS. By integrating clinical, biochemical, imaging, and genetic data, AI can simplify diagnosis, help find the condition earlier, and make diagnoses more accurate. In addition, AI enables more personalized care by finding metabolic and reproductive risk patterns that are unique to each patient and predicting how they will respond to treatment and what the clinical outcomes will be. This approach lets doctors customize treatments for each patient based on their specific needs, lifestyle, and other health problems [52, 53].Despite the obvious benefits of AI, its widespread use in clinical practice faces several challenges. Building datasets that accurately reflect all patient groups is challenging because of PCOS's variety, and AI models are highly dependent on the quality of the data they receive. When datasets are incomplete, biased, or contain measurement errors, the accuracy of predictions declines. High expenses and ongoing worries about data security, privacy, and informed permission also make implementation difficult. For these reasons, AI should be considered as a supportive tool rather than an independent diagnostic method. The results must always be evaluated using clinical experience as a guide[54,55].

Despite its current limitations, AI is still developing and has significant promise for PCOS diagnosis and treatment. To assure that clinical use is safe and can be repeated, it will be important to create consistent, explicit datasets and criteria for training algorithms [68]. As these foundations strengthen, AI may be able to support doctors more by making individual risk profiles more accurate and helping women with PCOS obtain more personalized prevention and treatment plans [55].

6. PCOS and Type 2 Diabetes: Modern Approaches to Metabolic Management

PCOS, in addition to its classical reproductive and hyperandrogenic characteristics, is strongly associated with several metabolic disorders, such as obesity, dyslipidemia, hypertension, and insulin resistance (IR), all of which greatly raise the risk of developing type 2 diabetes mellitus (T2DM) [56].Compared to other women without PCOS, those with the condition are much more likely to receive T2DM diagnosis. Because of this higher metabolic burden, it is important to have early and personalized treatment plans to avoid long-term problems. Along with lifestyle changes and metformin, new approaches including GLP-1 receptor agonists and CGM offer more precise metabolic control. CGM can discover trends in real time and predict short-term glucose levels when used with AI. This makes it simpler to control blood sugar levels and modify therapy more quickly[58]. AI makes personalization even better by combining CGM data with clinical, biochemical, and lifestyle factors to optimize nutrition advice, exercise plans, and medication strategies [59].

The combination of CGM and AI-driven analytics has led to the development of Digital Twin (DT) technology, a new tool for managing metabolic diseases. A DT is a virtual model of a person's metabolic state that is always being updated. It can simulate glycemic responses and predict how dietary, pharmacologic, or behavioral changes would affect a person before they are made. By combining CGM measures with data on nutrition, physical activity, sleep, and stress, DT systems may provide very personalized metabolic insights. Early studies in T2DM show that DT-assisted therapies improve glycemic outcomes and may reduce the requirement for medication, which suggests potential beneficial uses for women with PCOS who are at higher metabolic risk [60, 61].

Moreover, novel neuromodulation approaches such as transcutaneous auricular vagus nerve stimulation (ta-VNS) have shown promise as additional therapy in PCOS by improving insulin sensitivity via their antidiabetic effects [62]. Nevertheless, the integration of ta-VNS with AI-based monitoring is still in the experimental phase, and more clinical trials are needed to verifyits safety, effectiveness, and long-term therapeutic benefits [8].

7. Patient Education and Health Promotion Perspective

Digital health technology, like wearable gadgets, mobile apps, and continuous glucose monitoring, make patients more involved by letting them track their health in real time.

This helps patients notice changes early, make quick modifications to their lifestyle or treatment, and take a more active role in managing their condition [8]. Health education is important for managing PCOS and other metabolic diseases because it helps people understand better their condition and make smart choices about their everyday health habits. Based on this foundation, coordinated treatment from a team of professionals from different fields, such as doctors, dietitians, psychologists, and health coaches, provide consistent advice on medical, nutritional, emotional, and lifestyle issues [63, 64]. Public health and clinical guidelines highlight the need for unified care pathways that make sure early screening, evidence-based lifestyle advice, and easy access to psychological support are all available. This is in the line with the increased focus on patient education and integrated multidisciplinary support [65].

8. Discussion

Continuous glucose monitoring has improved glycemic control in patients with diabetes, and similar technologies are currently being investigated in the context of PCOS. Although integration of CGM and AI has been studied a lot in type 2 diabetes, studies including patients with both PCOS and its related metabolic complications remain limited. Recent research on PCOS continues to focus on AI-based diagnostic methods, especially those that integrate clinical, metabolic, and ultrasound-collected data that can improve phenotyping and enable early diagnosis [66]. However, current research faces significant limitations. Many studies depend on small, mixed groups of people, and the fact that there are not any standard methods makes it challenging to compare results. Women with PCOS are a very diverse group, with different phenotypes, ages, metabolic profiles, and comorbidities. Such diversity makes it difficult to create universally useful models [55]. Consequently, future research should focus on larger, well-defined groups [50], standardized AI protocols and prospective trials that test integrated CGM-AI strategies in women with PCOS who additionally have metabolic comorbidities like prediabetes or type 2 diabetes.

Modern digital technologies are useful for more than only diagnosing and predicting problems; they also have educational benefits. CGM and AI-based platforms offer real-time feedback, which can help patients better understand their condition. These features can encourage them to take care of themselves and get them more involved in making long-term lifestyle changes.

AI is also helping clinicians in creating treatment plans that are flexible and tailored to each person's metabolic responses, lifestyle, and risk factors. As a result, these technologies may allow for more accurate and proactive therapy, especially for patients who are more likely to have metabolic complications [67].

9. Conclusion

Digital technologies are changing endocrinology by making it easier and more accurate to diagnose and keep track of diseases. CGM and AI-based data allows clinicians to monitor metabolic trends all the time and create treatment plans that are unique to each person's needs. Using these technologies in the care of women with PCOS could lead to earlier diagnoses, better metabolic outcomes, and more patient involvement and self-management. This would help future generations avoid PCOS and improve long-term health. To fully achieve this potential, additional research is needed to develop standardized, clinically validated methods for introducing AI and CGM into the everyday care of PCOS. Larger prospective studies and consistent methodology will be essential for assuring safe, ethical, and evidence-based use of these new technologies.

Disclosure:

Author Contribution Statement

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In preparing this work, the authors used AI for the purpose of language editing and improving the clarity of the manuscript. After using this tool, the authors have reviewed and edited the content as needed and accept full responsibility for the substantive content of the publication.

AI tools were applied in this study for main functions: analyzing clinical reasoning narratives to identify linguistic indicators of specific logical fallacies, and refining the academic English of the manuscript to ensure clarity, coherence, and adherence to scientific writing standards. Additional AI-assisted linguistic polishing was performed to maintain proper grammar, style, and precision in the presentation of results.

All AI systems were used strictly as supportive instruments under human supervision. The final interpretation of data, classification of reasoning errors, and formulation of conclusions were carried out exclusively by experts in clinical medicine and formal logic. AI contributed only to improving efficiency in data processing, pattern recognition, and language refinement, without replacing human judgment at any stage of the analytical process.

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