ENDOCRINOLOGY RESEARCH AND PRACTICE

SOCIETY OF ENDOCRINOLOGY AND METABOLISM OF TURKEY

The Integration of Artificial Intelligence in Hormone Analysis: Transforming Diagnostic Precision and Personalized Endocrine Care

REVIEW
Endocrinol Res Pract. 2025 [epub ahead of print]

ABSTRACT

Traditional hormone analysis methods are often limited by single-point measurements, assay variability, and biological fluctuations that reduce diagnostic precision. Artificial intelligence (AI) offers powerful tools to address these limitations by recognizing complex hormone patterns, predicting physiological events, and guiding personalized treatment strategies. This review explores how AI enhances endocrine diagnostics across metabolic, reproductive, thyroid, and adrenal hormone domains. By integrating vast temporal datasets and interpreting subtle variations often missed by conventional methods, AI facilitates earlier detection of disorders such as diabetes, polycystic ovary syndrome (PCOS), thyroid dysfunction, and adrenal abnormalities. It also supports dose optimization and real-time monitoring. Artificial intelligence–driven tools are evolving to model multi-hormone systems, offering a holistic understanding of endocrine function and aiding clinical decision-making. The integration of AI into hormone analysis signifies a paradigm shift toward proactive, precise, and personalized endocrine care.

Keywords: Artificial intelligence, endocrinology, hormone analysis, machine learning

Introduction

Hormones are critical biological messengers that orchestrate physiological processes, including metabolism, growth, reproduction, and stress response. Precise hormone measurement and interpretation are essential for diagnosing endocrine disorders, monitoring treatment, and assessing overall systemic health. The growing prevalence of endocrine disorders has amplified the importance of hormonal analysis. Traditional methods often fail to capture the subtle variations and complex interactions that characterize these conditions.[1,2] Artificial intelligence (AI) offers unprecedented opportunities to analyze sophisticated patterns with enhanced precision and reliability.[3,4]

Artificial intelligence technologies have revolutionized medical diagnostics through advanced pattern recognition in hormonal data. Machine learning (ML) algorithms, particularly deep learning, excel at identifying subtle patterns within complex biological datasets. These systems process vast temporal data, integrate multiple parameters, and detect patterns imperceptible to human observers. Recent advances enable sophisticated models to analyze continuous hormone monitoring, interpret feedback mechanisms, and predict hormonal dysregulation before clinical manifestation.

Despite AI's transformative potential, existing studies remain fragmented across subdomains. This review consolidates advances in AI applications for hormone quantification and predictive analytics for endocrine dysfunction. It evaluates the clinical translatability of these technologies in endocrine care. By synthesizing interdisciplinary insights, the authors chart a roadmap for integrating AI into hormone analysis, advancing precision medicine tailored to individual patient profiles. This integration promises to overcome traditional diagnostic limitations, enabling more accurate diagnosis and personalized management of endocrine disorders.

Complications in Conventional Hormone Analysis and Pattern Interpretation

Methodological Limitations

Single-Point Measurements vs. Continuous Fluctuations: Conventional hormone analysis faces significant methodological limitations by relying on single-point measurements rather

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Received: April 29, 2025
Revision Requested: May 26, 2025
Last Revision Received: June 13, 2025
Accepted: July 4, 2025
Publication Date: August 19, 2025

Cite this article as: Selvam S, Manikandan S, Venkateswaramurthy N. The integration of artificial intelligence in hormone analysis: transforming diagnostic precision and personalized endocrine care. *Endocrinol Res Pract*. Published online August 19, 2025. doi:10.5152/erp.2025.25697.

DOI: 10.5152/erp.2025.25697

than capturing the complex temporal dynamics of hormone secretion. This approach fails to account for natural variations that significantly impact interpretation, as demonstrated by Collier et al[5] who found that healthy men's morning testosterone levels fluctuate approximately 19% between days, requiring a substantial 52% change between measurements to indicate clinical significance. Many hormones, including growth hormone (GH), are secreted in episodic pulses, meaning random sampling may coincidentally capture peaks or troughs, leading to potentially misleading results. Recent technological advances, exemplified by Bhake et al.'s[6] wearable microdialysis device capable of sampling free cortisol every 10-20 minutes over extended periods, have revealed consistent circadian patterns and stress-related spikes entirely missed by traditional testing methods, underscoring how richer temporal data collection provides more accurate hormone profiles and highlighting the critical need for continuous monitoring approaches in both research and clinical settings.[6]

Assay Variability and Analytical Errors: Hormone assays themselves introduce variability and inaccuracies. Immunoassay-based techniques, the workhorse of hormone testing, often suffer from limited specificity and calibration differences. Immunoassays may cross-react with structurally similar molecules or background proteins at low hormone concentrations, yielding erroneous results. For instance, Ohlsson et al[7] compared standard immunoassays to mass spectrometry (MS) for measuring estradiol in men and postmenopausal women. Immunoassays showed only moderate correlation with MS and were prone to interference. C-reactive protein levels correlated with estradiol readings by immunoassay but not by MS, suggesting that the immunoassay was detecting nonspecific signals. The authors concluded that many prior studies linking estradiol to clinical outcomes may need revaluation due to inaccuracies in immunoassays.[7] Lack of assay standardization is a related issue: different laboratories and kit manufacturers use varying antibodies and reference calibrators. As a result, the same patient's sample can yield different values across labs, and "normal ranges" are assay-dependent. A 2023 analysis highlighted divergent reference intervals between hormone assays, warning that such discrepancies could impact the management of endocrine disorders.[8]

Sample Handling and Stability: Certain hormones are chemically unstable in blood and can degrade or change before analysis. A prime example is adrenocorticotropic hormone (ACTH), a peptide prone to rapid proteolysis. Fraissinet et al[9] demonstrated that ACTH levels drop markedly unless samples are kept chilled and promptly processed. In whole blood at room temperature, ACTH became unreliable after just 2 hours, whereas cooling at 4°C preserved stability for up to 8 hours.

The timing of sample collection is another critical factor. Because of circadian fluctuations, drawing at inconsistent times introduces noise. Thyroid-stimulating hormone (TSH) varies by up to 40-50% over a day in a given individual. If 1 sample is taken at 8 AM and the next in the afternoon, a difference in TSH might reflect normal circadian decline rather than a true change in thyroid function.[10]

Physiological Noise and Biological Rhythms: The measurement of endocrine biomarkers presents significant challenges for clinical interpretation due to inherent biological variability. Cortisol exemplifies this complexity through its circadian rhythmicity, superimposed ultradian pulsatility, and acute responsiveness to psychological and physiological stressors. In healthy males, research demonstrates that the predominant source of variance in diurnal cortisol secretion derives from intra-individual fluctuations rather than consistent patterns.[11] Compounding these temporal dynamics, substantial inter-individual variability further complicates hormone assessment, with baseline concentrations often differing by an order of magnitude among healthy subjects of comparable demographics. Epidemiological data reveal 5- to 10-fold differences in hormone levels within healthy age- and sex-matched populations, challenging the utility of standardized reference intervals. This heterogeneity renders population means particularly problematic for individual assessment, as noted in 1 investigation where "remarkably few individuals showed the average" hormonal response during standardized stress testing.[12] The confluence of episodic secretion patterns, circadian oscillations, stimulus-dependent fluctuations, and pronounced inter-subject variability fundamentally constrains the diagnostic precision and reliability of isolated hormone measurements in clinical practice.

Diagnostic Challenges in Hormone Pattern Analysis

Inter-Individual Variation and Static Reference Ranges: The interpretation of hormonal measurements against conventional reference intervals poses significant diagnostic challenges due to inherent biological variability. Standard laboratory reference ranges, typically derived from population-based sampling, exhibit broad distributions that may inadequately reflect individual physiological states. This limitation stems from the concept of personalized homeostatic set points, wherein values within population-defined normal limits may represent pathological deviations for specific individuals. Collier et al[5] demonstrated this phenomenon using testosterone measurements, observing that reference intervals were "marginally useful" clinically—a 52% reduction in an individual's testosterone concentration could still fall within the reference range, potentially obscuring clinically significant alterations. This

MAIN POINTS

- Artificial intelligence addresses core challenges in hormone diagnostics, such as assay variability, circadian fluctuation, and inter-individual variability by modeling complex patterns and enabling continuous hormone monitoring.
- Artificial intelligence improves the accuracy of diagnosing endocrine disorders, including diabetes, PCOS, thyroid dysfunction, and Cushing's syndrome, by analyzing multivariate data and temporal hormone fluctuations.
- Artificial intelligence supports individualized therapy, such as levothyroxine and insulin dosing, through predictive modeling and decision-tree algorithms based on dynamic hormone profiles.
- Integration of artificial intelligence with biosensors and wearables enables real-time hormone tracking and prediction of physiological states like ovulation or stress responses, enhancing preventive care.
- Artificial intelligence is advancing beyond single-axis analysis to multi-system integration, facilitating the development of "digital twins" that simulate comprehensive endocrine function and guide holistic management strategies.

observation exemplifies the low index of individuality characteristic of many endocrine parameters, where intra-individual variance is proportionally small compared to inter-individual variance, diminishing the diagnostic utility of population-derived reference intervals for monitoring individual patients. Physiological life stages and comorbid conditions further complicate the interpretation of hormonal measurements. For instance, elevated insulin-like growth factor 1 (IGF-1) concentrations may suggest acromegaly, yet IGF-1 exhibits physiologically increased levels during puberty and pregnancy, while demonstrating suppression in states of malnutrition or uncontrolled diabetes mellitus.[10]

False Positives and Negatives in Lab Results: Endocrine diagnostics are significantly compromised by false-positive and false-negative results, with analytical interferences representing the predominant source of error. Macromolecular hormone complexes exemplify this phenomenon; these biologically inactive hormone aggregates produce spurious elevations in immunoassay measurements. Macroprolactin—a high-molecular-weight complex of prolactin bound to immunoglobulin G—constitutes a substantial fraction of total immunoreactive prolactin in certain individuals. Despite detection as "elevated prolactin" in standard immunoassays, macroprolactin lacks biological activity, resulting in patients without clinical manifestations of hyperprolactinemia. Epidemiological investigations have demonstrated that macroprolactin accounts for 15-26% of cases of biochemical hyperprolactinemia, representing misclassification rather than pathological hypersecretion. When unrecognized, this interference leads to erroneous diagnosis of prolactinoma and subsequent unnecessary therapeutic interventions. Paradoxically, extremely elevated hormone concentrations may generate false-negative results through the "hook effect" phenomenon. In 2-site immunometric assays, excessive analyte concentrations can simultaneously saturate both capture and signal antibodies, preventing sandwich formation and yielding paradoxically low measurements. Haddad et al[13] documented this phenomenon in patients with prolactin-secreting macroadenomas, where serum prolactin concentrations exceeding 60 000 nanograms per milliliter saturated assay systems, producing deceptively normal results.[13] Exogenous biotin supplementation—increasingly prevalent for purported dermatological benefits—represents an emerging analytical interference. High-dose biotin disrupts the biotin-streptavidin interaction, which is fundamental to many immunoassay platforms. Consequently, thyroid function tests in biotin-consuming individuals may present a biochemical pattern mimicking hyperthyroidism (artificially suppressed TSH and elevated thyroxine) despite clinical euthyroidism.[14]

Clinical Implications for Patient Management: The clinical implications of hormonal assay limitations extend beyond laboratory concerns to directly impact patient management and outcomes. Diagnostic uncertainty resulting from analytical inaccuracies may precipitate either delayed identification of endocrinopathies or erroneous diagnoses, consequently leading to inappropriate therapeutic interventions. For example, patients may be inappropriately committed to lifelong levothyroxine (LT4) supplementation based on falsely elevated TSH measurements or subjected to unnecessary pharmacological therapeutic intervention following misinterpretation of macroprolactinemia as a prolactin-secreting pituitary adenoma. Conversely, individuals with true adrenal insufficiency may be inappropriately reassured by indeterminate cortisol measurements, subsequently encountering potentially life-threatening adrenal crises. These analytical limitations similarly compromise therapeutic monitoring; significant day-to-day variations in TSH concentrations challenge optimal titration of hormone replacement therapies in hypothyroidism. In the context of endocrine neoplasia, the inherent variability in hormonal tumor markers (including cortisol and catecholamines) necessitates longitudinal trend analysis rather than isolated measurements for accurate clinical decision-making.[10]

In response to these constraints, AI applications have emerged as innovative solutions for enhancing the reliability and precision of hormonal analysis. These computational methodologies employ sophisticated algorithms to interpret complex patterns within multivariate datasets that might otherwise be overlooked by conventional analysis. Artificial intelligence platforms demonstrate the capacity for more accurate prediction of dynamic hormone concentrations, identifying subtle pattern abnormalities beyond human analytical capabilities, and providing decision support for individualized treatment strategies. This integration of computational intelligence into endocrine diagnostics establishes a foundation for more precise, efficient, and personalized patient management, effectively overcoming many of the traditional limitations of conventional hormonal testing methodologies.

Artificial Intelligence Technologies for Hormone Pattern Analysis

Artificial Intelligence in Metabolic Hormone Pattern Analysis: Artificial intelligence has made significant inroads into metabolic hormone analysis, particularly in recognizing patterns of insulin and glucose for the management of diabetes. Continuous glucose monitors generate high-frequency data that AI algorithms can analyze for trends beyond simple averages. For example, Chan et al[15] developed a ML framework to identify distinct patterns of blood glucose fluctuations from continuous monitoring in individuals with type 1 diabetes. The system extracted 6 recurrent glucose profiles using time-series clustering and identified that patients could be grouped into 4 phenotypic clusters, characterized by differing hemoglobin A1c levels and time-in-range outcomes.[15] Similarly, AI has been applied to predictive modeling: a recent study used features of the glucose curve during oral glucose tolerance tests to predict underlying metabolic defects. By analyzing the *shape* of glucose response curves, a ML model could accurately distinguish individuals with predominant muscle insulin resistance, beta-cell dysfunction, or impaired incretin response (AUC 88-95%). These results surpass traditional indices and suggest that AI pattern analysis of glucose dynamics can unmask the heterogeneity of metabolic syndrome and type 2 diabetes subtypes.[16]

Beyond glucose and insulin, AI techniques are being explored for appetite-regulating hormones such as leptin and ghrelin, which play roles in obesity and metabolic syndrome. Machine learning can integrate such hormonal cycles with clinical data to improve weight management strategies. In 1 study, researchers collected postprandial leptin and ghrelin *dynamics* along with other biomarkers in obese patients undergoing therapy. Using these features, they trained a predictive model for weight loss success on an appetite suppressant. The resulting model achieved about 80% accuracy in predicting 3-month weight reduction outcomes. Notably, it outperformed models relying solely on baseline metrics, such as body mass index, highlighting that incorporating hormone pattern features added predictive power.[17] Such an approach could help clinicians identify which patients are likely to respond to a given diet or pharmacotherapy by recognizing hormonal pattern signatures of treatment responsiveness. The integration of these appetite-regulating hormones into predictive frameworks represents a paradigm shift in metabolic health monitoring. Ghrelin, which exhibits characteristic peaks before meals following habitual feeding patterns, and leptin, which interact with circadian-metabolic disruptions commonly observed in obesity,[18-21] are now being incorporated into sophisticated algorithms designed to forecast blood glucose trajectories and preempt dysglycemic episodes. This evolving field represents a convergence of endocrinology, computational biology, and personalized medicine, with AI-designed compounds already showing success in targeting multiple receptors involved in appetite and weight control, offering unprecedented opportunities for precision-based metabolic health interventions and personalized obesity management strategies.

Artificial Intelligence in Reproductive Hormone Pattern Analysis: Reproductive endocrinology has leveraged AI to analyze the cyclical patterns of hormones that regulate menstrual cycles, ovulation, and fertility. Menstrual cycle tracking apps and wearables generate longitudinal data, including cycle lengths, basal body temperature, and changes in heart rate, that reflect underlying hormonal rhythms. Machine learning models have been designed to classify cycle phases and predict ovulation by detecting subtle physiologic pattern shifts. For example, a recent computational study utilized a neural network to analyze resting heart rate patterns throughout the cycle and successfully identified the luteal phase, inferring ovulation timing under free-living conditions.[22] This demonstrates how AI can non-invasively interpret signals downstream of hormones (e.g., estrogen's effect on basal heart rate) to flag cycle irregularities or anovulatory cycles. On the biochemical side, AI is directly used on hormone measurements for ovulation prediction. Li et al[23] developed ML models to pinpoint the day of ovulation in women undergoing fertility treatment by analyzing serial hormone levels. Using preovulatory trends in luteinizing hormone (LH), estradiol, and especially progesterone (P4), their algorithm predicted ovulation within a 24-hour window with up to 85% accuracy on a validation set. Interestingly, the model's interpretability analysis revealed that a rise in serum P4 (≥0.65 ng/mL) was the strongest predictor of imminent ovulation, surpassing even LH.[23] This insight, discovered through the ML evaluation of hormone patterns, could influence clinical practice by suggesting progesterone as a reliable marker for timing interventions (like insemination or egg retrieval) when LH is equivocal. Artificial intelligence-based ovulation forecasting tools are thus enhancing precision in fertility planning and assisted reproduction.

Artificial intelligence has also shown promise in detecting menstrual irregularities and reproductive disorders from hormone patterns. Polycystic ovary syndrome (PCOS), a common disorder characterized by chronic anovulation and hormonal imbalances, is an area of active AI research. Traditional diagnosis relies on a combination of clinical signs and static lab values; however, ML can better handle the complexity of PCOS presentation by integrating multiple hormonal and metabolic indicators. In a 2024 study, Zad et al[24] applied several ML algorithms to electronic health record data of women at risk for PCOS. Their best model, a neural network combining patterns in follicle-stimulating hormone, LH, estradiol, and sex hormone–binding globulin, achieved an area under the ROC curve of ~85% for predicting PCOS before a clinical diagnosis was made. The model learned that certain hormone constellations (e.g., an elevated LH: FSH ratio alongside high androgen levels) strongly indicated PCOS, whereas features like prior pregnancy (gravidity) weighed against it.[24] By recognizing these patterns, the AI could flag probable PCOS cases that clinicians had not yet diagnosed, facilitating earlier intervention. Beyond PCOS, researchers are exploring AI for other reproductive endocrinopathies. For instance, ML has been used to interpret subtle variations in menstrual cycle length and hormone profiles to predict conditions such as luteal phase defect, and even to differentiate types of ovulatory dysfunction. This augments clinicians' ability to diagnose disorders like PCOS or amenorrhea and to personalize fertility management (e.g., pinpointing the fertile window or optimizing hormone therapy in menstrual disorders).

Artificial Intelligence in Thyroid Hormone Pattern Analysis: Thyroid function is traditionally assessed through periodic blood tests (TSH, T3 [Triiodothyronine], T4 [Thyroxine]), but subtle patterns in these values over time or in relation to other biomarkers may go unnoticed. Artificial intelligence systems have been deployed to enhance the detection of thyroid dysfunction by mining routine laboratory data for patterns suggestive of hypo- or hyperthyroidism. For instance, Hu M et al utilized electronic health record data from thousands of patients to train ML classifiers for thyroid disorders. Their best model distinguished hyperthyroid and hypothyroid patients from euthyroid controls with high accuracy (AUROC 93.8% for hyperthyroidism, 90.9% for hypothyroidism).[25] Using a wide array of laboratory tests, including serum creatinine, mean corpuscular volume (MCV), and total cholesterol for hyperthyroidism, as well as serum creatinine, lactate dehydrogenase (LDH), and total cholesterol for hypothyroidism, is highly relevant for clinical endocrinologists. Thyroid dysfunction significantly alters renal function, with serum creatinine levels reflecting these changes. In hypothyroid patients, treatment reduces serum creatinine and improves estimated glomerular filtration rate (eGFR), indicating renal recovery. Hyperthyroid patients show increased serum creatinine and reduced eGFR after treatment.[26] In hypothyroidism, total cholesterol and LDL levels increase due to reduced clearance of low-density lipoprotein (LDL). High-density lipoprotein may remain normal or increase due to decreased CETP and hepatic lipase activity. In contrast, hyperthyroidism lowers total cholesterol, LDL, and apo B due to increased LDL receptor activity. High-density lipoprotein levels may decrease slightly in hyperthyroidism from enhanced lipid metabolism.[27] In hyperthyroidism, a mild decrease in hemoglobin and MCV is common, even in the absence of iron deficiency or anemia. MCV typically rises after treatment, indicating that low MCV is a consistent feature of active hyperthyroidism. Excess thyroxine alone does not replicate this MCV change. Autoimmune markers, such as thyroid microsomal and parietal cell antibodies, are frequently present.[28] The study found that serum LDH activity significantly increased in subclinical and clinical hypothyroidism ($P \leq .001$) compared to euthyroid individuals. Despite elevated LDH in hypothyroidism, there was no significant correlation between LDH and T3, T4, or TSH levels. Lactate dehydrogenase alterations may reflect metabolic disturbances, but are not reliable markers of thyroid dysfunction.[29] These correlations make clinical sense (e.g., hypothyroidism often raises cholesterol levels), and the AI effectively "learned" these relationships from the data. The authors concluded that ML could serve as a screening tool, scanning routine lab results to catch undiagnosed thyroid disorders in primary care.

Another key application of AI in thyroidology is optimizing LT4 therapy for patients with hypothyroidism. Achieving the correct LT4 dose after thyroidectomy or in chronic thyroiditis can be a trial-and-error process spanning months. Chen et al[30] created a ML decision tree to recommend LT4 dose adjustments after thyroidectomy. The model was trained on dose titration data from 320 patients, incorporating inputs such as current dose, TSH level, and patient characteristics. In validation, the AI's dose adjustment recommendation was within 1 standard dose increment (12.5 µg) of the optimal adjustment in ~75% of cases. This accuracy was on par with that of experienced endocrinologists and notably better than that of inexperienced providers or simple weight-based formulas. Essentially, the algorithm can predict that a patient with a very high TSH and a specific body weight might require, for example, an additional 25 µg. In contrast, another patient with a mild TSH elevation might need only +12.5 µg.[30] By following the decision tree's guidance, clinicians unfamiliar with complex thyroid cases could reach euthyroidism faster, reducing the symptomatic period for patients. Artificial intelligence-driven dosing tools like this could be integrated into electronic prescribing systems, providing personalized dose suggestions after each lab test. While physicians would remain in control, such tools offer a data-driven starting point for dose decisions. In the future, combining more data, such as genetic polymorphisms that affect thyroid hormone absorption or deiodination, could further refine AI dosing recommendations.

Artificial Intelligence in Pituitary and Adrenal Hormone Pattern Analysis: The pituitary and adrenal glands orchestrate hormone cascades with complex temporal patterns, and AI is being leveraged to model these for improved disease management. A prime example is Cushing's syndrome, a condition of chronic cortisol excess often due to an ACTH-secreting pituitary tumor. Diagnosing Cushing's syndrome can be challenging, requiring the integration of clinical features with multiple hormone tests (e.g., cortisol rhythms, dexamethasone suppression tests). Artificial intelligence–based decision systems are emerging to assist in this process. Recent work by Kalender et al explored various ML algorithms to classify Cushing's syndrome using retrospective clinical and biochemical data. Their best model, a Random Forest classifier, distinguished patients with Cushing's syndrome from those without it with ~92% accuracy (sensitivity of ~97%, specificity of ~87%). Moreover, the model could subclassify the type of Cushing's (e.g., Cushing's disease vs. ectopic ACTH vs. adrenal tumor) with high per-class precision by recognizing hormone pattern signatures associated with each subtype.[31] The AI effectively learned these distinctions. Such a tool could alert endocrinologists when a patient's constellation of lab results indicates Cushing's syndrome, or even suggest the likely subtype, thereby expediting confirmatory testing and treatment. Addison's disease (primary adrenal insufficiency), conversely, involves cortisol *deficiency* and can be life-threatening if missed. Although no large published human studies have yet been conducted, analogous ML models are being developed to screen for Addison's disease by analyzing routine laboratory patterns (e.g., concurrent hyponatremia, hyperkalemia, and elevated ACTH levels). The vision is an AI system that can raise an alarm for possible Addison's disease when a hospitalized patient's labs and symptoms follow a pattern exhibited by past Addison's cases, thus prompting a timely ACTH stimulation test. In veterinary medicine, such models already assist in identifying Addison's in dogs, and translation to human medicine is anticipated as data accrues.[32]

AI has also begun to tackle GH secretion patterns in pediatric and adult populations. Diagnosing growth disorders, such as GH deficiency, typically requires stimulation tests and serial sampling to observe the hormone's dynamic response. Researchers have been testing AI models on alternative datasets to reduce reliance on these labour-intensive tests. One innovative approach analyzed transcriptomic profiles (gene expression of dozens of genes) from a single blood draw and used ML to predict GH deficiency in children. In a pilot study, this method achieved an AUC of 0.97 in distinguishing GH-deficient children from those with idiopathic short stature. Essentially, the AI identified a gene expression "signature" in peripheral blood that correlates with inadequate GH secretion, providing a proxy for the standard GH stimulation test. Artificial intelligence can interpret multi-sample GH testing data more effectively than manual methods. For example, in acromegaly (GH excess), AI is being explored to detect the disease earlier by recognizing subtle pattern deviations in IGF-1 trends and symptom evolution.[33] Additionally, for patients on hydrocortisone or GH replacement, AI could potentially optimize dosing schedules by modeling the circadian pattern of cortisol or the desired pulsatility of GH and suggesting dose timing that mimics physiological rhythms. Although such advanced applications are still largely conceptual, early studies in Cushing's syndrome and GH disorders show that AI can enhance the authors' ability to decipher pituitary and adrenal hormone profiles. By doing so, it enhances the detection of disorders such as Cushing's syndrome, Addison's disease, and GH deficiencies, and paves the way for more physiologic management of these conditions.

Multi-System Artificial Intelligence Integration in Hormone Pattern Analysis: A frontier of endocrine AI research is the integration of multiple hormonal systems into unified models. Many endocrine disorders have systemic impacts or overlapping features (e.g., PCOS involves reproductive hormones and metabolic insulin resistance; Cushing's syndrome affects both adrenal and metabolic parameters). Artificial intelligence models that concurrently analyze patterns across endocrine axes aim to capture this complexity, thereby improving diagnostic accuracy and guiding holistic treatment strategies. One illustrative case is PCOS, which could be considered a multi-system disorder. The ML model for PCOS mentioned earlier combined ovarian hormone levels with metabolic indicators like obesity, rather than evaluating each in isolation.[24] By doing so, it could more reliably detect the condition than single-factor criteria, since PCOS manifests as a constellation of interrelated patterns (androgen excess, irregular gonadotropin levels, insulin resistance). This kind of integrated approach is also extending to other scenarios. Researchers are experimenting with AI that takes in a full panel of hormone results (thyroid, adrenal, gonadal, pancreatic) and clinical features to produce differential diagnoses. For instance, in a patient with fatigue and weight changes, such a model might simultaneously consider thyroid function, cortisol pattern, and sex hormones to determine if it's hypothyroidism, adrenal insufficiency, or perhaps perimenopause, with each diagnosis defined by a unique multi-hormone signature. Early evidence suggests that multi-input models can improve classification in complex cases: a meta-analysis of ML studies for central precocious puberty (an endocrine condition requiring both brain and ovarian hormone evaluation) found that models combining clinical data, laboratory hormone levels, and imaging data achieved a pooled accuracy with AUC ~0.90 in diagnosis.[34] This underscores that integrating diverse data sources (hormonal and otherwise) gives a more complete picture and better performance than any single source alone. "Digital twin" for endocrine health: a composite AI simulation of a patient's endocrine network, continuously updated with multi-hormone data, that can test how a change (such as a new medication or lifestyle change) might affect the entire hormonal balance. While still experimental, such models have been trialed in metabolic disease and have shown improved outcomes in tailoring treatments.[35]

Artificial Intelligence Solutions for Single-Point Measurement Limitations

AI offers solutions by enabling continuous monitoring, predictive modeling, and real-time analytics that transcend static snapshots. For example, wearable biosensors paired with AI can now continuously track hormone-related biomarkers, providing richer datasets than those obtained through periodic blood draws. In the diabetes domain, continuous glucose monitors linked with AI-driven insulin pumps (a "closed-loop" system) demonstrate the power of real-time data integration. These systems significantly improve glycemic control compared to intermittent fingersticks.[36] Analogously, emerging AI-enhanced wearables for stress and sleep hormones (like cortisol and melatonin) allow noninvasive continuous hormone monitoring, offering real-time insights beyond what a single lab cortisol level can show.[37]

This study demonstrated that by inputting a patient's age, cycle day, and a couple of hormone readings, an AI algorithm could pinpoint the person's position in the menstrual cycle with 95% confidence.[38]

Similarly, an innovative pilot study in dancers demonstrated that AI modeling of menstrual hormone variation, using only 2 blood samples per cycle, provided a "dynamic and comprehensive picture" of each dancer's hormone network and detected subtle hormonal disruptions well *before* traditional symptoms or cycle changes appeared.[39] For instance, AI-driven platforms have been utilized to personalize hormone therapy dosing in real-time. One study reported an AI algorithm that adjusted menopausal hormone replacement dosages based on continuous symptom and biomarker tracking, resulting in improved efficacy and patient satisfaction.[40]

Reducing Assay Variability Through Artificial Intelligence

Another challenge in hormone analysis is assay variability, where results can differ due to changes in reagent lot, calibration drift, operator technique, or instrument error. Such variability undermines the trustworthiness of serial hormone measurements. Artificial intelligence-based calibration and quality control tools are now helping to stabilize this inconsistency. For example, laboratories are implementing *AI-driven quality control* systems that continuously learn from patient data to detect analytical errors or drifts in real-time. In a 2024 study, Dong et al[41] introduced an AI-powered patient-based real-time quality control (AI-PBRTQC) for laboratory assays, including hormones such as thyroxine and anti-Müllerian hormone, and found it to be more efficient in identifying quality risks than traditional quality control methods. This type of intelligent QC can promptly identify an assay calibration issue or reagent degradation, prompting corrective action before patients are affected. The AI-PBRTQC approach maintained high sensitivity while minimizing false alarms, indicating a robust performance in stabilizing assay outputs.[41] Figure 1).

AI algorithms are also being applied to calibrate assays and mitigate interference. For instance, an AI-based "delta check" method developed by Zhou et al.[42] used deep learning to compare current and prior results, effectively catching specimen mix-ups that conventional delta checks missed.[43] Additionally, AI can integrate data from multiple assays to cross-verify hormone levels. By combining outputs from different platforms (e.g., an immunoassay and a MS result for the same sample), ML models can identify outliers or apply bias corrections, thus harmonizing measurements across methods. In summary, AI-based calibration models and real-time QC mechanisms are reducing assay variability by detecting errors early, adjusting for shifts, and ensuring that hormone measurements remain accurate and comparable over time.[41,43] These improvements enhance the reliability of hormone tests, which is crucial for longitudinal monitoring and nuanced dosing decisions in clinical practice.

Integrating Artificial Intelligence with Advanced Assay Technologies

Mass spectrometry can simultaneously quantify multiple hormones and metabolites with high accuracy, but it yields complex datasets. Machine learning is increasingly used to interpret MS-based profiles and extract clinically useful information. In thyroid disease research, Che et al[44] showed that combining MS-based multi-omics (proteomic and metabolomic data) with AI can reveal patterns not evident from single analytes. In their review, they note that ML algorithms, such as random forests and support vector machines, applied to large omics datasets enable more accurate classification of thyroid conditions by integrating subtle biomarker combinations.[44] This type of multi-omics integration enables an AI to weigh dozens of hormonal and metabolic markers simultaneously, rather than clinicians interpreting each hormone individually. The result is a more holistic and precise assessment, for instance, differentiating thyroid carcinoma from benign nodules by a composite "fingerprint" of hormone levels and protein markers. Similarly, in adrenal endocrinology, researchers have used ML on steroid hormone panels (measured by liquid chromatography–MS) to improve the detection of subclinical cortisol excess. In 1 study of adrenal tumor patients, an ML model analyzed 17 urinary steroid metabolites and correctly stratified patients by cortisol secretion status and cardiometabolic risk, outperforming single metabolite thresholds.[45] These examples underscore AI's role in distilling high-dimensional assay data into clinically actionable insights.

Artificial Intelligence technologies are accelerating the evolution of hormonal biosensor capabilities, with significant implications for continuous monitoring applications. Novel wearable and point-of-care analytical platforms now enable the real-time quantification of hormones from non-invasive biological matrices, including saliva, perspiration, and interstitial fluid. These advanced monitoring systems generate continuous data streams, necessitating sophisticated computational approaches for signal processing and interpretation. Machine learning algorithms play a crucial role in calibrating sensor outputs, mitigating signal noise and temporal drift, and converting raw electrochemical signals into clinically relevant hormonal metrics. Contemporary research has yielded wearable cortisol monitoring systems that utilize minimally invasive microneedle arrays or electrochemical detection methodologies, capable of generating continuous profiles of adrenocortical hormones. Artificial Intelligence

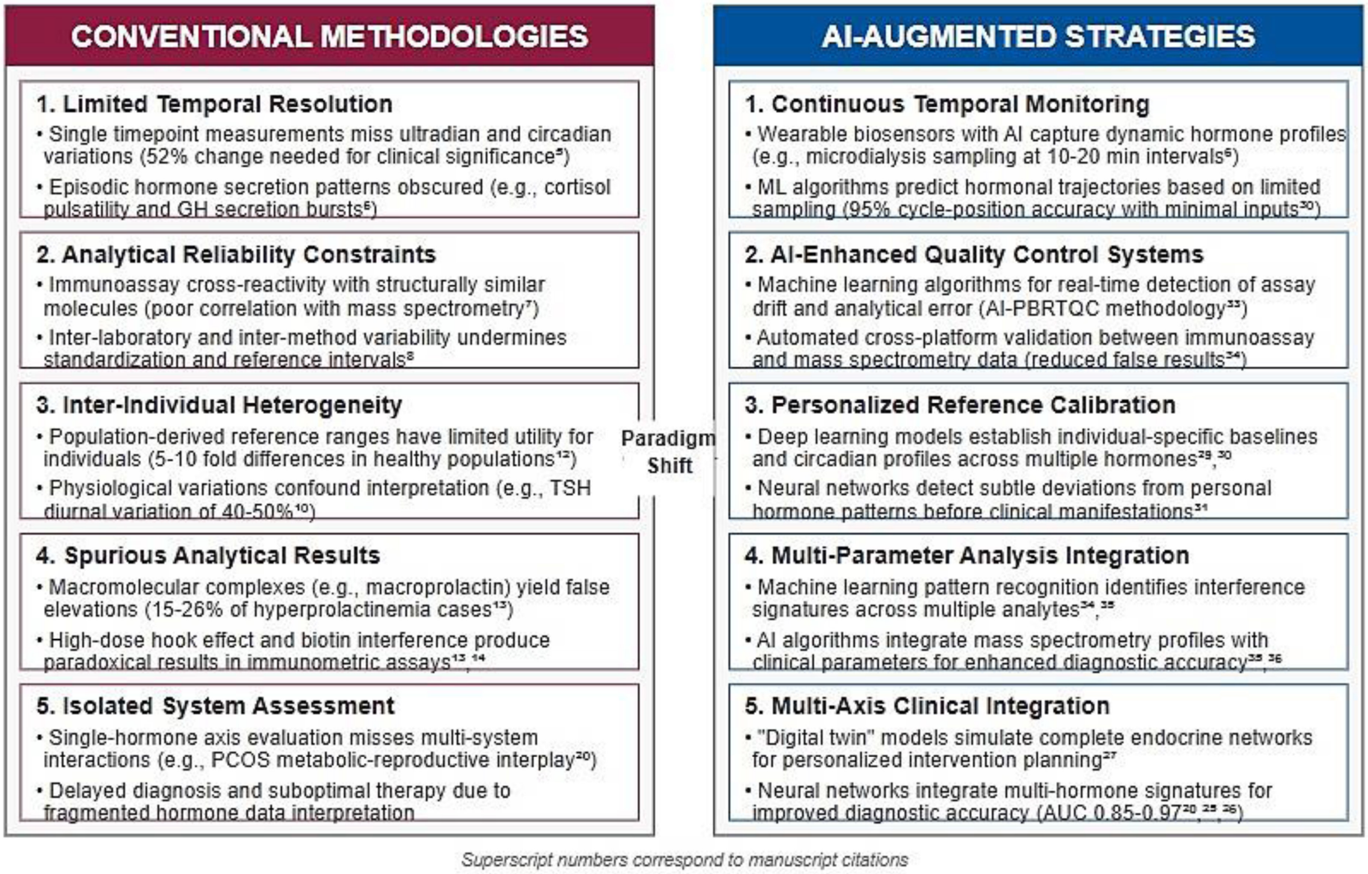

Figure 1 . Paradigm shift: from conventional limitations to artificial intelligence–enhanced hormone analysis.

calibration frameworks subsequently adjust for confounding physiological variables, such as perspiration rate and cutaneous temperature, to ensure that measured values accurately reflect plasma cortisol concentrations.[37,46] Through enhanced signal processing capabilities, AI substantially improves the analytical performance of these biosensors, accelerating their transition to clinical implementation. Furthermore, cloud-based analytical platforms enable the contextual interpretation of continuous hormonal data, identifying, for example, anomalous cortisol elevations during expected nadir periods, which facilitates therapeutic adjustments in patients with adrenal insufficiency. The integration of AI extends to laboratory automation systems, where clinical facilities adopting MS platforms for comprehensive steroid profiling benefit from computational optimization of analytical workflows, compensating for batch-related variability, automating result validation, and algorithmically determining when confirmatory testing methodologies are indicated. Current literature suggests that future MS platforms incorporating AI decision support systems "could be a game-changer in assay interferences" and analytical accuracy.[43] Artificial Intelligence further demonstrates significant utility in multimodal data integration, synthesizing hormonal measurements with diverse clinical parameters spanning symptomatology, radiological findings, and genomic markers. Exemplifying this approach, computational models now integrate continuous glucose monitoring data with insulin measurements and physical activity metrics to generate nuanced assessments of diurnal insulin resistance patterns that transcend conventional static measurements. In oncology applications, deep learning algorithms have demonstrated the capacity to predict hormone receptor status directly from standard histopathological images, potentially obviating the requirements for additional immunohistochemical assays. Shamai et al.[47] documented that neural network architectures accurately predicted estrogen receptor positivity from breast neoplasm morphology on hematoxylin and eosin-stained specimens, achieving concordance with standard receptor immunoassays.

Handling Biological and Circadian Variability

Hormone levels are not static; they fluctuate in daily circadian cycles (e.g., cortisol peaks in the early morning, while melatonin peaks at night). They can pulsate or vary in response to menstrual or other biological rhythms. This biological variability poses a challenge: a "normal range" for a hormone like cortisol depends on the time of day, and a value considered low at 8 AM might be perfectly normal at midnight. Artificial intelligence is now enabling more sophisticated modeling of temporal patterns, helping clinicians interpret hormone levels in the context of an individual's biological clock. One application is using AI for circadian rhythm modeling—algorithms can analyze time-series hormone data to characterize an individual's rhythm and detect deviations. For example, Gubin et al[37] discuss how new sensor technologies, which inform AI algorithms, enable personalized chronobiological analysis. Large repositories of continuous wearable data can be integrated with AI to enhance the interpretation of circadian health, enabling personalized chronodiagnosis.[38]

Conclusion

AI-driven analysis of hormone patterns is revolutionizing the field of endocrinology by uncovering insights that were previously unattainable with conventional approaches. Across metabolic, reproductive, thyroid, and adrenal systems, ML models have demonstrated the ability to detect subtle temporal patterns and multivariate hormonal signatures that correlate with disease states or treatment outcomes. These tools are enabling earlier diagnosis, more precise prediction of physiological events (such as ovulation or glycemic excursions), and data-informed personalization of treatments (like optimized insulin or LT4 dosing). The integration of multiple hormonal axes into unified models represents the next leap forward, promising to handle the complex interplay in systemic endocrine disorders and comorbidities. However, translating these AI technologies into routine clinical practice will require overcoming certain challenges. Ensuring model interpretability and transparency is crucial for clinician trust, especially when AI recommendations affect medical decisions. Techniques like explainable AI are beginning to shed light on which hormone features drive an algorithm's predictions. Additionally, robust validation in diverse patient populations is necessary to prevent biases and maintain accuracy across various age groups, ethnicities, and clinical scenarios. Data privacy and integration hurdles must also be addressed, as effective AI often relies on large-scale, longitudinal data that span electronic health records and wearable sensors. Despite these challenges, the trajectory of current research suggests that AI will become an invaluable adjunct to endocrinologists. By continuously learning from new data and refining its pattern recognition, AI can keep improving diagnostic algorithms and predictive models. In doing so, it has the potential to augment clinical decision-making, offering second opinions on challenging diagnostic puzzles, monitoring patients in real-time for dangerous hormonal fluctuations, and suggesting optimal interventions tailored to each individual's hormonal profile. Ultimately, the synergy of endocrinology expertise with AI may usher in an era of more proactive, precise, and personalized endocrine healthcare, where hormone fluctuations are managed with a level of insight and responsiveness that was once unimaginable.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer reviewed.

Author Contributions: Concept – S.M.; Literature Search – S.S.; Writing – S.M.; Critical Review – N.V.

Acknowledgements: The authors extend their heartfelt thanks to the authors' research guide, Dr.N.Venkateswaramurthy, for their valuable mentorship, encouragement, and constructive feedback, which were instrumental in the successful completion of this research. The authors' appreciation also goes to the faculty members and technical staff of the department for their assistance and insightful discussions. Lastly, the authorsare thankful to the participants and community membersfor their cooperation and willingness to contribute to this research.

Declaration of Interests: The authors have no conflicts of interest to declare.

Funding: This study received no funding.

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