Exploring Late-Onset ADHD in Women: A Data-Driven Approach Using AI and Socio-Demographic Analysis

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Abstract

Due to internalized symptoms and social masking, women are often diagnosed with ADHD later in life, making gender differences in diagnosis a significant and understudied topic. AI is being increasingly used to enhance diagnostic tools and uncover intricate patterns in behavioral, neuroimaging, and medical record data, although the majority of applications do not stratify data by gender. This disparity could unintentionally strengthen preexisting biases in conventional diagnostic systems. To determine whether and how AI-based approaches to ADHD diagnosis consider gender differences, we conducted a systematic review of the literature in this study. We examine peer-reviewed studies that utilize AI methods across various data modalities between 2013 and 2025. Studies are categorized by publication time, gender focus, AI methodology, and data type. Our analysis reveals that, although AI has the potential to enhance diagnostic precision, the lack of gender-specific evaluation remains a significant drawback. We contend that to guarantee more equitable mental health results, particularly for historically underdiagnosed populations like women with ADHD, future AI systems should specifically include gender-sensitive design and demographic fairness.

Introduction

Attention-deficit/hyperactivity disorder (ADHD) is a prevalent neurodevelopmental disorder that can persist into adulthood and typically initially appears in childhood. It is typified by recurrent patterns of impulsivity, hyperactivity, and inattention that impede growth or functioning [1][2]3]. Because of its varied presentation, which can change depending on age, gender, and the presence of concomitant diseases, diagnosing ADHD is still a challenging undertaking [2][3][4]. Complex datasets, including behavioral testing, medical records, and neuroimaging research, can now be analyzed thanks to recent developments in AI, especially machine learning [5][4]. These developments could enhance conventional diagnostic techniques and provide a more in-depth understanding of unique profiles [7].

A serious issue still exists despite the expanding corpus of research: women are still underdiagnosed with ADHD [8][5][6]. Historically, male-dominant samples have been used to establish and evaluate diagnostic definitions and instruments, which frequently fail to capture the more internalized, less disruptive symptom profiles that women and girls typically display [7][8]. For many women with ADHD, this gender prejudice reinforces long-term unfavorable outcomes and unmet clinical needs by contributing to delayed diagnosis, frequent misdiagnosis, and inadequate treatment [3][9][10]. The question of whether AI technologies exacerbate or mitigate current diagnostic disparities is gaining attention as they are increasingly incorporated into clinical decision-making processes [5]. The use of AI in ADHD research has been the subject of several recent reviews, such as those by du Randt, who explored ADHD in women and discussed unique challenges and misdiagnosis issues [9]. Other notable reviews include those that concentrate on explainable AI for ADHD prediction [19][20], on computational screening approaches using behavioral and questionnaire data [16][17][18], on diagnosis using structural and functional neuroimaging data [12][14][15], and on AI applications for children with

ADHD [11]. These critiques, however, frequently ignore model performance across demographic subgroups, especially gender, in favor of concentrating primarily on technical performance and overall correctness. Therefore, there is still a significant knowledge gap on whether AI-based techniques might lessen gender-based diagnostic discrepancies or if they run the risk of reinforcing the same biases found in traditional evaluations.

This review closes that gap by examining the use of AI techniques in gender-focused ADHD research. Specifically, we examine studies that analyze data from behavioral surveys, neuroimaging, and electronic health records using AI methods that go beyond machine learning, including approaches to symbolic reasoning or rule-based decision systems. We investigate whether different AI techniques identify or lessen gender-based disparities in ADHD diagnosis, and we point out methodological flaws and potential research directions. This study additionally examines whether the included papers disclose model fairness metrics, do gender-specific subgroup analyses, or address representational biases in their training data, all of which are informed by recommended practices described in recent equity-focused AI frameworks [11]. These factors are crucial for guaranteeing fair healthcare results as well as for evaluating AI accuracy. This review attempts to elucidate AI's present and potential role in promoting more inclusive and equitable diagnostic methods for ADHD by combining findings from various modalities and periods.

Methods

A thorough, organized literature analysis was carried out to examine how AI technologies have been used to diagnose ADHD in women, as well as whether these approaches lessen or maintain gender-based diagnostic inequalities. Peer-reviewed research published between January 2013 and July 2025 was the focus of the search, which was conducted using PubMed and Google Scholar. The Boolean search query that was utilized was this: ("Attention Deficit" OR "ADHD") AND ("machine learning" OR "artificial intelligence") AND ("gender" OR "women" OR "sex differences") AND (diagnosis OR detection OR classification). Finding papers that used AI or machine learning to diagnose ADHD and also reported sex-specific results or included gender-based analyses was the goal of the inquiry.

Only English-language full-text publications with human subjects were included. We used inclusion criteria based on two important review studies to ensure high methodological reliability and relevance: the review on AI-based ADHD detection by Garg et al. (2022) [11], which described validated AI approaches across neuroimaging, behavioral, and physiological modalities, and the systematic review of gender differences in adult ADHD by Thapar et al. (2022) [10], which focused on sex-disaggregated analysis in functional impairments. These requirements must be fulfilled by eligible studies: (1) applying AI/ML models (such as SVM, random forests, and deep neural networks) and (2) employing these models to diagnose ADHD or classify its symptoms. Research that (a) only employed standard statistical techniques, (b) did not present any gender-based data or analysis, or (c) were reviews, opinion pieces, or conference abstracts lacking complete results were not included. Two reviewers independently screened abstracts and titles after duplicates were eliminated. Eligibility disagreements were settled by consensus. We looked at the gender representation (the percentage of female participants), the AI methodology (traditional ML, deep learning, ensemble models, NLP), the data modality (behavioral scales, EEG/MRI, EHR, wearable sensors), and the model performance metrics (accuracy, sensitivity, specificity, AUC, F1 score) of each eligible study. By Thapar et al. [10], we also evaluated if the research documented trends in misdiagnosis, functional consequences, or gender-specific symptom patterns. The data types (behavioral, neuroimaging, EHR, multimodal), AI approach, degree of gender-specific reporting (none, partial, full), and publication years (2013–2017, 2018–2022, 2023–2025) were used to group the studies for ease of comparison. A detailed, evidence-based summary of how AI is currently addressing or ignoring gender gaps in ADHD diagnosis was made possible by this methodology.

Results

Utilizing the search criteria described in the Methods section, we found 9 papers describing AI solutions for automatic ADHD diagnosis. These studies were grouped by data type, AI type, gender, year of publication, and key findings. The results are shown in Table 1.

Table 1. Results of literature search grouped by data type, AI type, year of publication, gender, and key findings.

	Year	Gender (M/F/Both)	Data Type	AI Type	Key Findings
[13]	2012	Both	MRI	Machine Learning	Accuracy was increased by multimodal models; gender was used but not examined independently.
[15]	2013	Not specified	MRI	Machine Learning	High accuracy (90.18 percent ELM); no study of gender.
[18]	2020	Not specified	Questionnaire	Machine Learning	87% accuracy; gender was not examined, but was added as a predictor.
[17]	2022	Both	Questionnaire	Machine Learning	There was no gender-specific analysis; TRAQ10-based models performed well.
[12]	2023	Both	MRI	Machine Learning	75% categorization accuracy;

					results were not based on gender.
[14]	2023	Both (analyzed separately)	MRI	Not specified (dFNC analysis)	Discovered that children and adults with ADHD had different brain connectivity depending on their sex.
[19]	2024	Both	Questionnaire	Machine Learning	90% accuracy; no subgroup analysis was performed; however,2 genders were included as a feature.
[20]	2024	Both	Physiological	Machine Learning	SVM; 81.6% accuracy; no gender-stratified analysis;
[16]	2025	Both	Questionnaire	Machine Learning	SVM: AUC 0.96, accuracy ~85%; no gender-stratified analysis; RF: AUC 0.99.

Three studies used AI classification models using MRI data as the main input [13][15][12]. Without identifying the participants' gender or doing a gender-based analysis, one study that used extreme learning machines (ELM) obtained a diagnosis accuracy of 90.18% [15]. Another study included both male and female participants and used multimodal models to increase accuracy, although gender was not investigated separately [13]. Using MRI and machine learning algorithms, a more recent study reported 75% categorization accuracy; however, it did not examine outcomes by gender [12]. The first MRI-based investigation to specifically stratify results by gender was conducted in 2023. The study used dynamic functional network connectivity (dFNC) analysis and discovered sex-specific variations in brain connections between children and adults with ADHD [14].

Data from questionnaires were used in five studies to classify ADHD [18][17][19][16]. When gender was included as a predictor but not examined independently, a 2020 study used machine learning to reach 87% accuracy [18]. Another study that used TRAQ10-based models in 2022 did not undertake gender-specific analysis, although it did perform well [17]. Although both genders were included as features in the model, a 2024 study that used questionnaire data achieved 90% accuracy without performing subgroup analysis [19]. Both SVM (AUC 0.96, accuracy ~85%) and random forest models (AUC 0.99) performed well on questionnaire data, according to a 2025 study; however, no gender-stratified findings were given [16].

Only one study, which achieved an accuracy of 81.6%, classified ADHD using physiological cues, such as cardiac and electrodermal characteristics, in combination with SVM [20]. Despite the inclusion of both male and female subjects, no analysis was done specifically for gender. This study underscores the need for larger, more varied samples while highlighting the growing significance of physiological signs as possible objective markers of ADHD.

Gender-specific analyses were generally lacking in all of the research. Only one study performed a sex-stratified analysis and discovered gender variations in brain connectivity, despite the fact that the majority comprised both male and female subjects [14]. Other studies either included gender as a model component without stratified evaluation [18][19][20], recorded gender without additional analysis [13] [12][17], or did not report gender at all [15]. The dearth of gender-specific insights in existing AI-assisted ADHD research is a significant gap.

Discussion

Due in large part to the more obvious hyperactive and impulsive characteristics that are commonly linked to ADHD, male participants have historically dominated ADHD research. A distorted picture of ADHD that underrepresents female symptomatology resulted from early diagnostic criteria and treatment regimens that were centered on male symptom patterns [9]. Consequently, research findings are frequently not applicable to women with ADHD, particularly when they involve neuroimaging or behavioral analysis. By concentrating mostly on men, we run the risk of ignoring the more subtle, frequently internalized symptoms that are more prevalent in women, like anxiety, daydreaming, and emotional dysregulation.

Although both male and female volunteers are increasingly frequently included in studies, our data demonstrate that gender disparities are often not thoroughly investigated. The approach of not examining gender differences explicitly ignores the distinct symptom patterns of women with ADHD, even if it offers a more balanced sample. In addition to displaying more internalized symptoms like emotional dysregulation, women frequently report a greater prevalence of comorbidities like anxiety and depression [1][6]. When AI models are created, these gender differences are routinely overlooked, which could reinforce diagnostic models that are centered on men. The way ADHD presents differently in women may be missed by AI systems educated on non-gendered data, which could reinforce preexisting biases. The growing emphasis on research that particularly looks at gender variations in ADHD diagnosis is one tactic that could help reduce gender-based diagnostic disparities. Emotional discomfort and co-occurring mental health disorders are more common in women with ADHD than in males, according to research [5][6][9], and machine learning algorithms may identify these gender-specific differences [7**].** Female ADHD patients may have more accurate diagnoses if AI models take into consideration their particular symptom profiles. Nevertheless, despite the encouraging promise, some research indicates that there is a chance of reinforcing preexisting gender prejudices if AI models are not created with these gender inequalities in mind. AI systems trained exclusively on datasets of male patients may not adequately reflect the more complex symptom profiles seen in women [11].

The necessity for gender-specific strategies is highlighted by recent court cases showing that women are underdiagnosed with ADHD. There will probably be a greater push in future research toward studies that are only focused on women, as these difficulties highlight differences in diagnostic procedures. This is in line with the expanding movement in AI research to prioritize gender-inclusive data. Particularly in identifying ADHD in women, where conventional diagnostic techniques frequently fall short, improved diagnostic accuracy has been demonstrated by AI models designed to differentiate between male and female symptom presentations [12][14][19]. However, AI systems run the danger of making the problem of underdiagnosis or misdiagnosis worse if gender is not sufficiently taken into account in the training data, especially when trained on datasets that are primarily male [12].

Future studies should look at gender-specific data from a variety of modalities, such as multimodal, behavioral, neuroimaging, and EHR databases (including behavioral, neuroimaging, EHR, and multimodal data). When it comes to treating the complexity of ADHD symptoms in women, each technique has special benefits. Future AI models can more accurately represent the variety of ADHD symptomatology and lessen diagnostic inequities by including gender considerations into various data modalities.

Conclusion

We carried out a thorough literature analysis to look into how gender differences, more especially, the underdiagnosis of women, are taken into account by AI-based approaches to ADHD diagnosis. Nine pertinent peer-reviewed studies that were published between 2013 and 2025 were found. Data modalities (MRI, questionnaires, physiological signals), AI techniques (SVM, RF, ELM), the year of publication, and the degree of gender-specific analysis were all taken into consideration while analyzing these studies. Our results show that even though AI diagnostic accuracy can reach 90%, gender-sensitive analyses are still rare. While the other studies either ignored gender reporting or only considered it as a demographic variable, only one study performed sex-stratified analysis. Ignoring gender-specific analysis reinforces preexisting diagnostic biases and ignores significant clinical differences in female ADHD. Fairness metrics, sex-disaggregated results, and balanced representation in training data must be given top priority in future studies. If these steps are not taken, underdiagnosed groups, particularly women, may continue to be overlooked, which could lead to the continuation of disparities in mental healthcare.

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