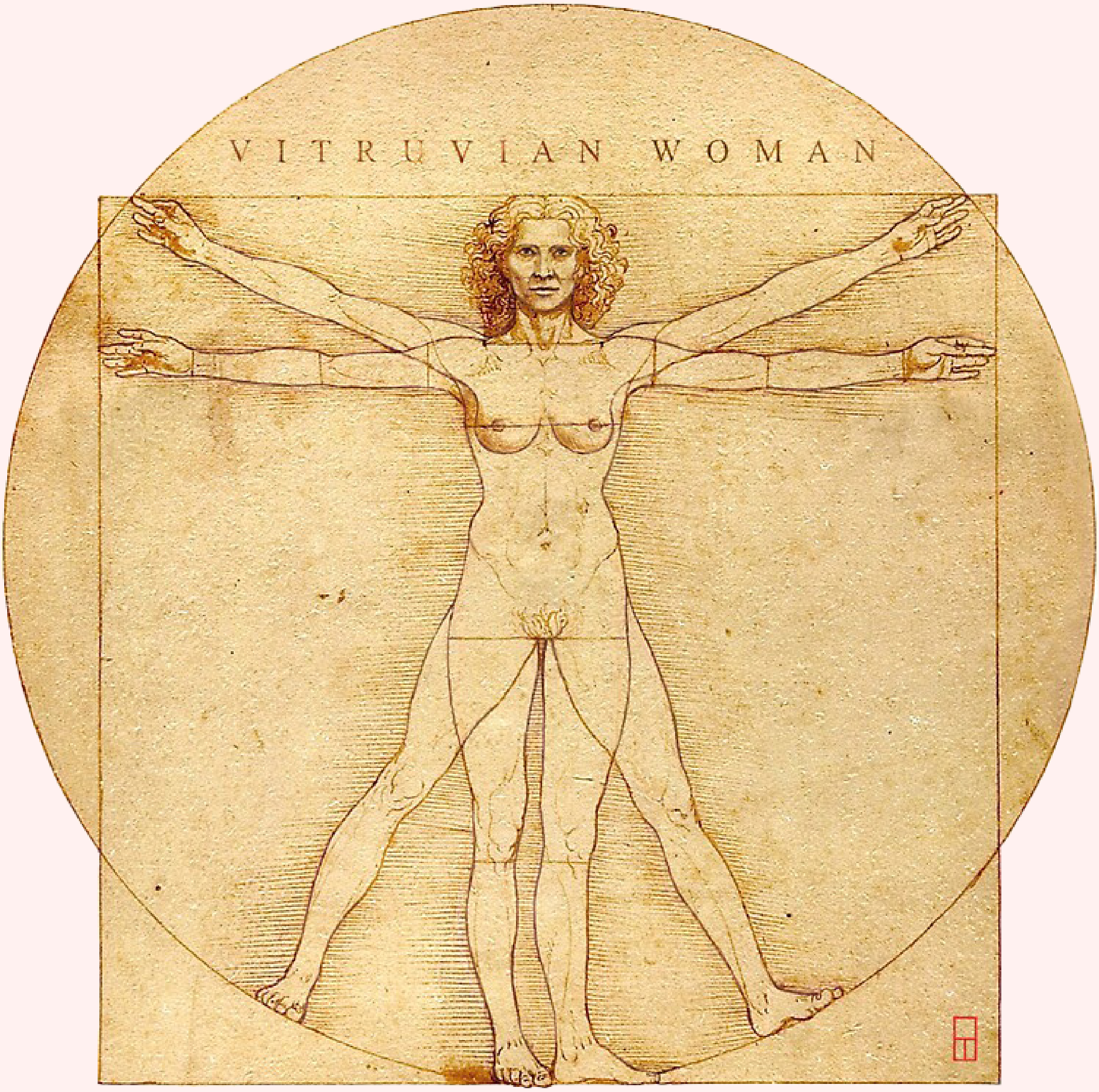

From Margins to Momentum: An AI-Enabled Transformation in Women's Health

Dr. Bita Sehat, Dorothy Chou, and Dr. Nina Rawal

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Summary

The Trillion-Dollar Blind Spot: Reimagining Women's Health Through AI

Neglecting women's health comes at a staggering cost, one measured not only in human suffering but also in lost economic potential. For decades, chronic underinvestment and gender bias in medicine have left women systematically underserved by healthcare systems that were never built with their needs at the center. This is more than a public health issue; it's a trillion-dollar blind spot. The World Economic Forum estimates that closing the women's health gap could add at least $1 trillion in global economic output annually by 2040[1]. In other words, addressing women's health is not just a moral imperative but an economic opportunity of immense scale.

Behind every statistic is a personal struggle. Women often wait years for diagnoses, like the one who endured nearly a decade of pain before learning she had endometriosis. Others, such as women experiencing heart attacks, are misdiagnosed because their symptoms don't match male-centric profiles. In fact, women are 50% more likely to be misdiagnosed and sent home[2-3]. These aren't rare cases; they are the result of a system that fails to account for women's distinct biology and health needs.

We now stand at a pivotal moment. Artificial Intelligence offers a powerful opportunity to uncover and address the deep-rooted problems in women's healthcare. These include data deserts in conditions that affect only women, data gaps in diseases that mostly affect women, and data bias in conditions that affect women differently. While these issues have persisted for decades, new tools like synthetic data, wearables, and sex-aware algorithms provide the means to close these gaps. Fertility care offers a glimpse of what's possible when robust data meets advanced technology: better predictions, higher success rates, and improved outcomes. The data exists. The tools exist. What comes next depends on whether we choose to apply them with the urgency and intention this moment demands.

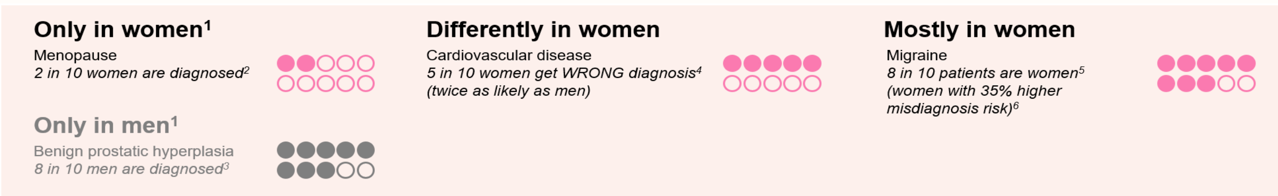
Introduction

Data Deserts and Biased Blueprints: The Consequences of Overlooking Women in Health Data

A major barrier to innovation in women's health is the lack of robust, representative data. While AI holds transformative potential, its effectiveness depends entirely on the quality and completeness of the data it is trained on. In the realm of women's health, the data gap is not just wide; it is deeply entrenched.

Historically, women have been underrepresented in clinical research, frequently excluded from early-phase trials due to outdated concerns about hormonal variability or reproductive risk. Well into the 1990s, clinical studies often treated the male body as the default, operating under the flawed assumption that women are simply "smaller men"[4]. This has led to datasets that default to male physiology and disease patterns. Even when women are included, critical sex-specific variables are often inconsistently recorded or entirely overlooked. The tangible consequences of this bias are clear. As illustrated in Exhibit 1, it can lead to a higher likelihood of misdiagnosis and delayed diagnoses for conditions that primarily affect women. The result is a silent ceiling on discovery: AI systems trained on incomplete or biased data risk perpetuating the very inequities they aim to solve.

Exhibit 1. The Human Toll of Diagnostic Inequity: Misdiagnosis and Delays in Women's Health

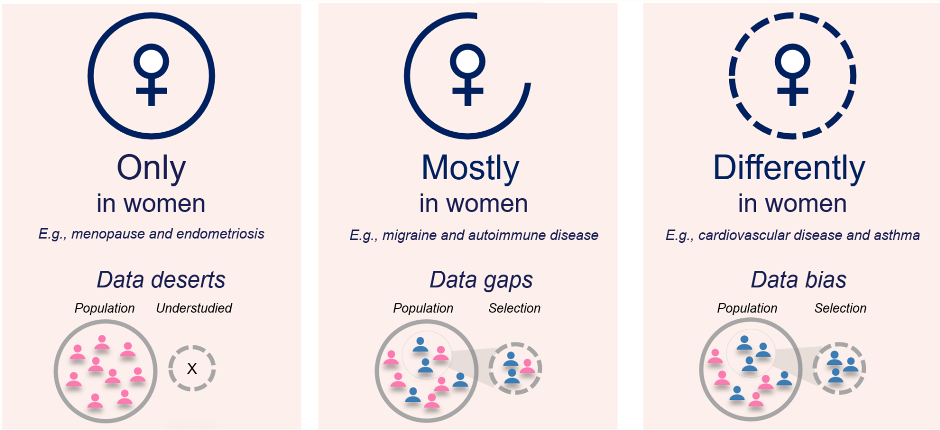


Adopted from McKinsey & Company (2023), Exhibit 3 in the article "Closing the data gaps in women's health", https://www.mckinsey.com/industries/life-sciences/our-insights/closing-the-data-gaps-in-womens-health 2. Best, C., et al. (2015). Prevalence of menopausal symptoms among mid-life women: Findings from electronic medical records. BMC Women's Health, 15(1), 1–5 3. Muntner, P., et al. (2024). Forecasting the Burden of Cardiovascular Disease and Stroke in the United States Through 2050. Prevalence of Risk Factors and Disease: A Presidential Advisory From the American Heart Association. Circulation, 149(10), e743–e847 4. Al Hamid, A., et al. (2024). "Gender Bias in Diagnosis, Prevention, and Treatment of Cardiovascular Diseases: A Systematic Review", Cureus,15;16(2) 5. Al-Hassany, L., Haas, J., & van den Maagdenberg, A. M. J. (2020). Giving Researchers a Headache – Sex and Gender Differences in Migraine. Frontiers in Neurology, 11, 549038 6. Jensen, A., et al. (2020). Chronobiology differs between men and women with cluster headache; clinical phenotype does not. Neurology, 94(14), e1499–e1509

Understanding Women's Health Data Gaps

Using the FemHealth Framework (© 2019 FemHealth Ventures[6]), we classify women's health conditions into three categories: Only in women, Mostly in women, and Differently in women. We'll use this framework to explore the data deficiencies AI must address to drive meaningful progress.

Exhibit 2. A Framework for Understanding the Women's Health Data challenge



Data Deserts – The "Only in Women" Crises

These are conditions biologically unique to women, such as endometriosis, polycystic ovary syndrome (PCOS), and menopause, high-quality data remains limited. In these areas, AI currently has limited capacity to fuel discovery because the foundational datasets simply do not exist. A notable exception is infertility, which stands out due to decades of structured, mandated data collection (e.g. national IVF registries)[7-8]. But for most conditions only affecting women, the challenge is not just a research gap - it is a complete data desert.

Data Gaps – The "Mostly in Women" Mysteries

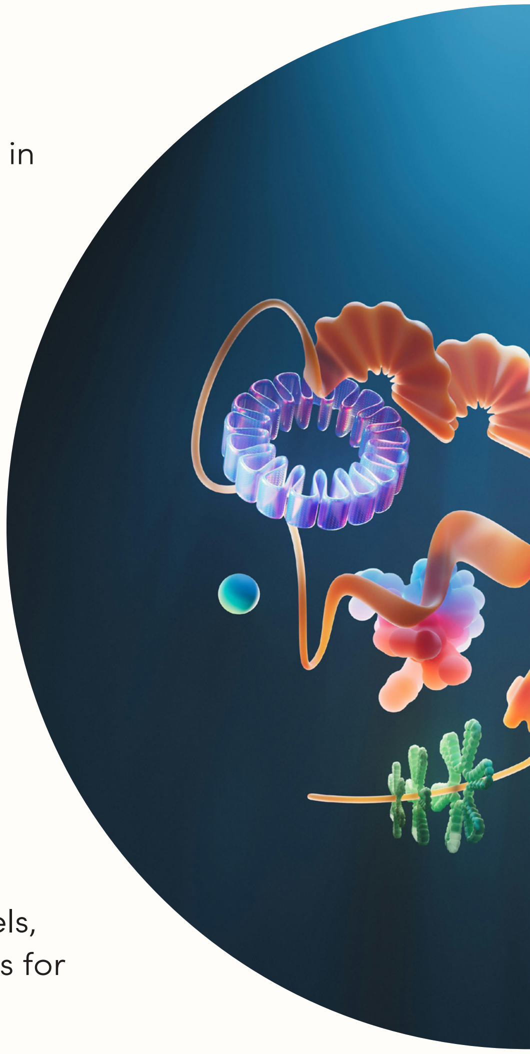
These conditions affect both sexes but disproportionately impact women, such as autoimmune diseases, migraines, and chronic fatigue syndrome. In the Mostly in Women category, the challenge isn't a lack of data but a lack of detail. Data are often not disaggregated by sex, obscuring critical differences in onset, progression, and treatment response. Without this granularity, AI struggles to detect patterns unique to women, missing key opportunities to improve outcomes. For example, if migraine datasets don't capture menstrual cycles or hormonal status, AI may overlook a major trigger. Women's experiences get lost in averages.

Data Bias – The "Differently in Women" Dangers

The Differently in women category includes conditions that affect both sexes, such as heart disease, asthma, and diabetes. For decades, research and diagnostics were calibrated to the male norm, overlooking female-specific differences. For example, women with cardiovascular disease often experience nausea, fatigue, or jaw pain rather than the "classic" chest pain in men[9]. The consequences are real: Zelnorm (tegaserod) was withdrawn in 2007 after data revealed it increased heart attack and stroke risks in women that male-dominated trials had missed[10]. AI trained on such skewed data risks reinforcing these blind spots, amplifying inequities rather than fixing them.

Charting the New World and Leapfrogging the Past

AI presents not just an opportunity to catch up, but to leap ahead. Because women's health has been under-addressed for so long, the field is unconstrained by legacy systems and outdated infrastructure, uniquely positioned to adopt cutting-edge, AI-driven tools from the outset. However, realizing this potential requires more than optimism, it demands a focused, actionable strategy. One that seizes short-term opportunities while laying a strong foundation for long-term, transformative breakthroughs. Below, we outline strategic priorities in each category (Only, Mostly, Differently in women) for harnessing AI, charting a new course that leapfrogs the failures of the past.



Only in women: Unlocking Existing Data Goldmines

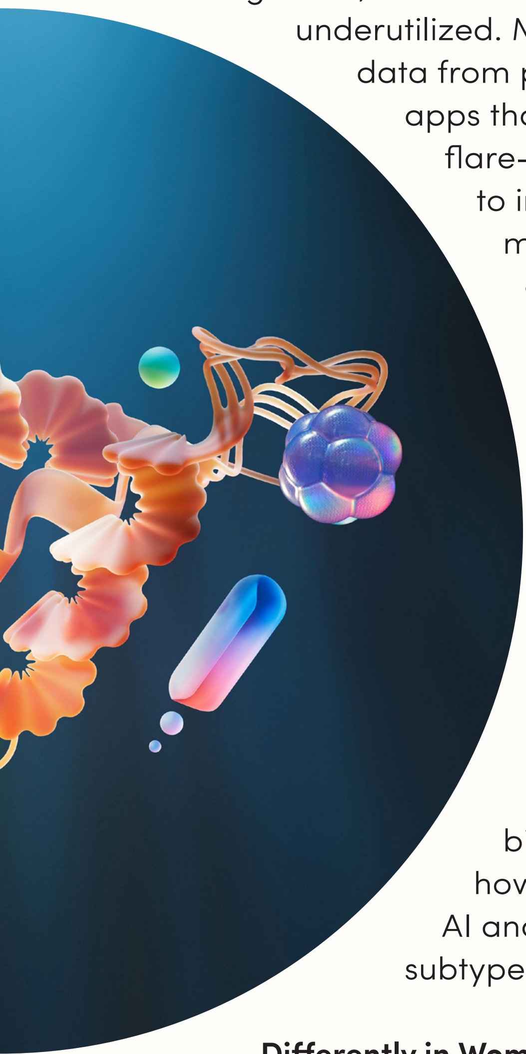
Here and Now: Infertility offers a strong starting point for AI in women's health, supported by rich, structured data. Unlike many other women-specific conditions, fertility medicine has a significant advantage in that it is supported by a wealth of rich, structured data, collected over many decades. National registries, mandatory reporting, and sustained collaboration between public institutions and private stakeholders[7–8] have created a rare, high-quality data goldmine capable of supporting AI-driven innovation. AI models trained in fertility registries have already improved IVF success rates by better predicting individual responses to treatment[11–13].

Machine learning algorithms can analyze a couple's profile and prior cycle data to personalize hormone dosing or select the embryo most likely to implant, thereby increasing the odds of a live birth. In fact, recent studies have demonstrated that AI-driven, clinic-specific IVF prediction models outperform traditional national models, leading to more precise counseling and higher success rates for patients[14].

Looking Ahead: For other women-specific conditions like endometriosis, where clinical data is limited, a promising approach is AI-generated synthetic data: artificially created datasets that statistically resemble real-patient data. Synthetic data can help fill critical gaps when real-world data is scarce. This approach has proven effective in other domains. For example, synthetic data has improved AI accuracy in lung cancer detection[15], and one study found that models trained on synthetic liver tumor images performed as well as those using real data[16]. Applying similar methods to endometriosis (e.g. generating synthetic pelvic MRI scans or laparoscopic images with endometriotic lesions) could bolster AI's ability to recognize and diagnose the disease. Additionally, leveraging patient-generated data (symptom-tracking apps, wearables) and advanced text mining of clinical notes can uncover patterns even when formal studies are lacking. By augmenting limited real data with synthetic data and creative data sources, we can begin to strengthen diagnostic tools and research for conditions that have long been neglected. The goal is to ensure that no women's health issue remains a blind spot simply because of sparse data.

Mostly in women: Addressing the Invisible Majority

Here and Now: Many diseases that disproportionately affect women such as migraines, autoimmune disorders, thyroid conditions – are data-rich but underutilized. Migraines, for example, have an abundance of real-world data from patient anamneses, wearables, and symptom-tracking apps that can be leveraged to improve diagnosis and predict flare-ups. AI can unlock valuable insights from these datasets to improve care. Early studies show promise in forecasting migraine attacks using hormonal cycles, stress levels, sleep quality, and environmental data[17]. Such predictions could allow women to prepare or take preventative medication before pain strikes. To deliver real-world impact, these predictive tools must be integrated into care through patient-facing apps, digital coaching, and clinician dashboards to enable timely, personalized intervention.



Looking ahead: In conditions that primarily affect women, the greatest potential lies in moving from symptom management to mechanism-based insight. By combining real-world data from electronic health records, genomics, and digital tools, advanced AI can help uncover disease subtypes, identify female-specific biomarkers, and discover new therapeutic targets. Consider how this approach has transformed breast cancer care, where AI analysis of genomic and clinical data has identified molecular subtypes and enabled more personalized, effective treatments[18-19].

Differently in Women: Uncovering Sex-Based Gaps in Common Conditions

Here and Now: Across conditions such as cardiovascular disease, diabetes, and asthma, vast datasets are available. The problem is that they are often analyzed without accounting for sex-specific differences, which masks key variations in symptoms, progression, and treatment response. AI offers a critical opportunity to re-examine this data through a sex-informed lens. AI can also help detect subtler sex-based patterns that clinicians might overlook. In diabetes, for example, research indicates there are differences in how the disease progresses or complications manifest between men and women[20]. In asthma, hormonal fluctuations are known to play a role: asthma prevalence flips from higher in boys pre-puberty to higher in women in adulthood, and women tend to have

more severe asthma after puberty[21]. Yet treatment protocols often don't account for menstrual cycle effects or pregnancy-related asthma changes. AI models mining clinical data could uncover, for instance, that women's asthma hospitalizations spike at certain cycle phases or that blood sugar control in diabetic women is affected by hormonal contraception. The data is already available in electronic health records, biobanks, and wearables; what's needed now is a deliberate effort to analyze it in ways that reflect women's unique health profiles and drive more equitable care.

Looking ahead: The next step in this domain is to bake sex-specific analysis into how we collect, label, and interpret health data. It's not enough to do a one-time retrospective analysis; we must proactively design studies and AI systems that consider sex as a fundamental variable. practically, it means curating training datasets for AI that are balanced and labeled by sex and developing algorithms that are validated separately on male and female populations. For example, cardiovascular risk models could be refined by incorporating female-specific factors such as pregnancy history (e.g. conditions such as preeclampsia, which are known to heighten later heart disease risk) and inflammatory markers.

Conclusions

A Pivotal Opportunity to Leap Ahead and Deliver Real Results

By uniting the transformative power of AI with purposeful data generation and sex-aware analysis, we have a unique chance to revolutionize women's health and close long-standing gaps. This approach can deepen our understanding of female physiology, illuminate how women differ in health and disease, and unlock innovative solutions that improve care and outcomes for generations to come. Already here and now, existing data holds untapped insights that could drive meaningful improvements in women's health.

The question is no longer if AI will reshape healthcare, but whether we will have the foresight to direct its power toward our most overlooked challenges. We do not need to follow the slow path of the past. We can leap forward into a new era of health. Let us be the generation that makes it happen.

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Bita Sehat is a Partner at Trill Impact Ventures. She is passionate about supporting companies that use big data and AI to transform human health, with a strong interest in women's health innovation. Previously, she was an Investment Director at Industrifonden and held roles in business development, strategic partnerships, and healthcare consulting. She currently serves on the board of Minervax, a women's health company. Bita holds an MSc in Biomedicine and a PhD in Molecular Oncology from the Karolinska Institute, along with postdoctoral research experience at Karolinska and McGill University. She also earned an MBA in Strategy and Business Valuation from Concordia University.

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