International Journal of Leading Research Publication (IJLRP)
E-ISSN: 2582-8010 ● Website: www.ijlrp.com ● Email: editor@ijlrp.com

Data Integrity and Digital Health Systems as Drivers of Women's Socio-Economic-Political Empowerment

Biswajit Bhoi[1], Dr. Rajeev Johari[2]

[1]PhD Research Scholar, [2]Professor
[1,2]Department of Economics, Sikkim Skill University, Sikkim, India

Abstract:
The intersection of women's health and their socio-economic and political empowerment is a multifaceted domain where physiological well-being acts as a prerequisite for societal participation. Access to accurate health information and reliable healthcare infrastructure is fundamental to this empowerment, yet the data underpinning women's health is frequently characterized by measurement errors, sparsity, and privacy risks. This paper examines the role of health data integrity and emerging digital technologies in facilitating or hindering women's agency. We argue that while digital tools and longitudinal studies offer pathways to empowerment through better health management, they are currently compromised by algorithmic hallucinations, privacy vulnerabilities, and methodological biases. By synthesizing recent advancements in statistical calibration, FemTech privacy analysis, and Large Language Model (LLM) benchmarking, we propose a comprehensive framework for validating the information ecosystems that women rely upon. We conclude that socio-economic-political empowerment cannot be fully realized without first resolving the "validity crisis" in women's health data and digital interfaces.

1. INTRODUCTION

Background and Motivation

The socio-economic and political empowerment of women is inextricably linked to their physical and mental health. Health acts as a foundational capability; without it, participation in the workforce, education, and political discourse is severely constrained. In the modern era, information itself has become a critical resource for this empowerment, where access to scholarly and practical health knowledge facilitates economic prosperity and the enrichment of "liberated minds" (Das, 2014). However, the landscape of women's health is undergoing a digital transformation, shifting from traditional clinical settings to mobile applications and Artificial Intelligence (AI) driven interfaces. These technologies promise to democratize access to reproductive and general health management, potentially allowing women to optimize their participation in public life by managing their biological needs more effectively.

Problem Definition and Scope

Despite the promise of digital health, a significant problem lies in the reliability and safety of the data and tools currently in use. Women's health data is often "asynchronous and error-prone," making it difficult to derive accurate longitudinal insights necessary for long-term health planning (Chang et al., 2022). Furthermore, the rise of "FemTech" and health-tracking applications has introduced severe privacy risks, where sensitive reproductive data is collected without adequate security, exposing women to legal and social harms (Saini & Saxena, 2024). Additionally, the integration of Large Language Models (LLMs) into health advisory roles has revealed alarming rates of "hallucinations" and medical errors, which can lead to misguided decisions that jeopardize health outcomes (Penny-Dimri et al., 2025). The scope of this paper is to analyze these technological and methodological barriers and propose a framework that ensures health interventions truly serve the goal of empowerment.

Insufficiency of Existing Approaches

Current approaches to women's health data analysis and information dissemination are insufficient for two primary reasons. First, traditional observational research and naive statistical adjustments often fail to capture the ground truth of health risks, as demonstrated by the discrepancies between observational studies and randomized clinical trials regarding hormone therapy (Petitti & Chen, 2008). Second, the rapid deployment of digital health tools has outpaced regulatory and validation frameworks; for instance, standard uncertainty metrics like perplexity in AI models fail to capture meaning-level inconsistencies in medical advice, rendering them inadequate for high-stakes women's health scenarios (Penny-Dimri et al., 2025).

Contributions

This paper makes the following contributions to the field:

1. We establish a theoretical linkage between robust longitudinal health data analysis and socio-economic empowerment, demonstrating how statistical improvements in handling "noisy" data can lead to better policy and individual decision-making.
2. We propose a multi-layered validation framework that integrates functional data calibration, privacy auditing, and semantic entropy evaluation to ensure that digital health systems function as safe instruments for empowerment rather than vectors of risk.

2. RELATED WORK

2.1 Methodological Challenges in Longitudinal Health Data

A significant portion of women's health research relies on longitudinal studies, which track cohorts over time to understand aging, disease progression, and reproductive health. However, these datasets are frequently plagued by measurement errors and irregular sampling intervals. Research by Chang et al. highlights that time-varying covariates in women's health studies, such as the Study of Women’s Health Across the Nation (SWAN), are often not measured synchronously with responses, leading to estimation biases when naive methods are used (Chang et al., 2022). Similarly, Zhang and Chen emphasize the complexity of "mixed longitudinal studies," where subjects enter at different ages, necessitating advanced nonparametric covariance estimation to reconstruct valid functional trajectories (Zhang & Chen, 2017). The reliability of self-reported outcomes is another critical weakness; Gu et al. note that self-reported data in large-scale initiatives often suffer from imperfect sensitivity and specificity compared to diagnostic tests (Gu et al., 2015). This body of work underscores that without rigorous statistical correction—such as functional calibration—policy decisions regarding women's health may be based on flawed premises, thereby undermining empowerment initiatives that depend on accurate health baselines.

2.2 Digital Health Technologies (FemTech) and Privacy

The digitization of women's health through mobile applications offers a direct route to empowerment by giving women control over their reproductive data. Liu et al. demonstrated the feasibility of using large-scale app data to predict pregnancy probabilities, showing that digital tracking can meaningfully stratify fertility risks and aid in family planning (Liu et al., 2018). However, this technological empowerment is double-edged. Saini and Saxena reveal that the privacy policies of many reproductive health apps are opaque, often gathering personally identifiable information (PII) and sensitive healthcare data without explicit security measures (Saini & Saxena, 2024). The potential for this data to be exploited—legally or commercially—poses a threat to women's socio-political safety. Unlike the statistical literature which focuses on data accuracy, this category of work highlights the vulnerability of the *user* in the digital ecosystem, suggesting that empowerment is impossible if the tools used for health management compromise the user's privacy and security.

2.3 Artificial Intelligence and Information Integrity

As women increasingly turn to AI for health information, the integrity of these systems becomes paramount. Das argues that information flow is a key driver of socio-economic empowerment for marginalized communities (Das, 2014). However, recent studies indicate that General Purpose AI models often fail in the medical domain. Gruber et al. introduced a "Women's Health Benchmark" for LLMs, revealing high failure rates in specialties like obstetrics and gynecology, particularly concerning missed urgency and medication errors (Gruber et al., 2025). Furthermore, Penny-Dimri et al. show that traditional methods for detecting AI errors are insufficient, proposing "semantic entropy" as a superior metric for identifying hallucinations in women's health advice (Penny-Dimri et al., 2025). This research creates a clear contrast to the "big data" optimism of earlier years; while data availability has increased (as seen in (Carillo et al., 2019) regarding Philippine health data), the *quality* of automated interpretation has become a critical bottleneck. This work posits that for AI to support empowerment, it must move beyond mere information retrieval to guaranteed semantic accuracy.

3. METHOD/APPROACH

To address the challenges of data reliability and system safety in women's health, we propose the **Trusted Health-Empowerment Framework (THEF)**. This framework is designed to validate the data and tools used to inform women's health decisions, ensuring they form a solid basis for socio-economic planning.

3.1 Framework Architecture

The THEF consists of three integrated modules:

1. **Longitudinal Data Calibration Module:**
    - *Objective:* To rectify asynchronous and error-prone health data collected from women over time.
    - *Mechanism:* Utilizing the functional calibration approach proposed by Chang et al., this module treats health metrics (e.g., hormone levels, blood pressure) as functional data. It applies functional principal component analysis (FPCA) to calibrate unobserved synchronized values from observed, noisy data (Chang et al., 2022).
    - *Rationale:* Naive analysis (e.g., last-observation-carried-forward) introduces bias. Accurate historical health trajectories are essential for predicting future capacity for economic participation.
2. **Privacy and Security Audit Module:**
    - *Objective:* To assess the risk profile of digital health interfaces (FemTech apps).
    - *Mechanism:* This module implements a static and dynamic analysis pipeline as described by Saini and Saxena. It scans for PII leakage, checks permission requests against functional necessities, and evaluates compliance with privacy policy declarations (Saini & Saxena, 2024).
    - *Rationale:* Socio-political empowerment is negated if health tools become surveillance devices.
3. **Semantic Integrity Verification Module:**
    - *Objective:* To filter and validate AI-generated health advice.
    - *Mechanism:* This module employs the "semantic entropy" metric to detect hallucinations (Penny-Dimri et al., 2025). It cross-references outputs against the "Women's Health Benchmark" covering obstetrics, gynecology, and primary care (Gruber et al., 2025).
    - *Rationale:* Misinformation in health prevents informed decision-making, directly impacting a woman's ability to manage her health alongside professional obligations.

3.2 Evaluation Plan

To evaluate the effectiveness of the THEF, we propose a hypothetical deployment using a mixed longitudinal dataset similar to the SWAN study structure (Chang et al., 2022)(Zhang & Chen, 2017).

- **Dataset Construction:** We would aggregate anonymized, self-reported health outcomes (e.g., cycle tracking, symptom logs) from a mobile platform (Liu et al., 2018) and clinical records.

- **Metric 1: Error Reduction:** We will compare the variance in health trajectory estimation before and after applying the Calibration Module. Success is defined by a statistically significant reduction in estimation bias, similar to the asymptotic properties described in (Chang et al., 2022).
- **Metric 2: Safety Score:** We will run the Privacy Audit on the top 10 most-used FemTech applications in the target demographic. A "Safety Score" will be generated based on the absence of OWASP vulnerabilities and PII leakage (Saini & Saxena, 2024).
- **Metric 3: Advisory Accuracy:** Using the benchmark from Gruber et al., we will feed patient queries to the system. Success is achieving a hallucination rate below 5% as measured by semantic entropy (Penny-Dimri et al., 2025)(Gruber et al., 2025).

4. DISCUSSION

Practical Implications and Deployment

The implementation of rigorous data validation in women's health has profound practical implications for empowerment. Accurate health modeling allows for better preventive care, reducing the incidence of chronic diseases like cardiovascular issues or diabetes, which are often silent and detected too late via self-reporting (Gu et al., 2015). When women can rely on "liberated minds" enriched by accurate knowledge (Das, 2014), they are better positioned to negotiate flexible working conditions and plan for long-term career growth. Furthermore, identifying underlying components of health infrastructure—such as the importance of safe water supply and local health stations (Carillo et al., 2019)—enables policymakers to target investments that yield the highest return on women's socio-economic stability.

Limitations and Failure Modes

Despite the proposed framework, several limitations persist:

- **Self-Reporting Bias:** Even with statistical calibration, the root source of data often remains self-reported. As noted by Petitti and Chen, statistical adjustment cannot always compensate for fundamental confounding or erroneous inputs in observational research (Petitti & Chen, 2008).
- **Computational Complexity:** The nonparametric covariance estimation required for mixed longitudinal studies (Zhang & Chen, 2017) and the calculation of semantic entropy for LLMs (Penny-Dimri et al., 2025) are computationally intensive. This may limit the deployment of these solutions in resource-constrained environments where low-end devices are prevalent.
- **Data Heterogeneity:** Health determinants are multidimensional and vary significantly by geography (e.g., the specific provincial determinants in the Philippines (Carillo et al., 2019)). A model trained on Western populations (like the SWAN study) may not generalize globally.

Ethical Considerations and Risks

The intersection of health data and technology introduces significant ethical risks. The most pressing is the privacy paradox in FemTech: while these tools empower women with knowledge, they simultaneously expose them to "legal consequences" if reproductive data is subpoenaed or sold (Saini & Saxena, 2024). Additionally, reliance on AI for health advice poses a liability risk. If an LLM provides incorrect dosage or treatment advice—a common error type identified in the Women's Health Benchmark (Gruber et al., 2025)—the resulting harm could be catastrophic. There is also the risk that reliance on automated predictions (e.g., pregnancy probability (Liu et al., 2018)) could lead to over-confidence in algorithmic contraception or fertility planning, resulting in unintended life-altering outcomes.

Future Work

Future research must focus on two avenues. First, there is a need to expand "Women's Health Benchmarks" to include more diverse languages and cultural contexts to ensure global applicability (Gruber et al., 2025). Second, statistical methods must evolve to better handle the "measurement error" in self-reported outcomes without relying exclusively on expensive diagnostic tests (Gu et al., 2015). Developing lightweight, on-device algorithms that can perform functional calibration (Chang et al., 2022) without compromising user privacy would be a critical step toward secure and empowered health management.

5. CONCLUSION

The role of women's health in their socio-economic-political empowerment is foundational, yet it is currently threatened by a fragile information ecosystem. This paper has argued that empowerment is contingent upon the integrity of health data and the safety of the digital tools used to manage it. By examining the limitations of observational studies (Petitti & Chen, 2008) and the risks of modern FemTech (Saini & Saxena, 2024), we demonstrated that access to information alone is insufficient; the information must be accurate, secure, and statistically robust. The proposed approaches—ranging from functional calibration of longitudinal data (Chang et al., 2022) to semantic entropy checks for AI (Penny-Dimri et al., 2025)—offer a pathway to stabilize this ecosystem. Ultimately, ensuring the reliability of women's health data is not merely a technical challenge but a political imperative, as it secures the biological foundation upon which socio-economic agency is built.

REFERENCES:

1. Das, Anup Kumar (2014). The 7 Habits of Highly Effective Research Communicators. https://arxiv.org/pdf/1409.3920v1
2. Chang, Xinyue, Li, Yehua, & Li, Yi (2022). Asynchronous and Error-prone Longitudinal Data Analysis via Functional Calibration. https://arxiv.org/pdf/2209.13807v2
3. Saini, Shalini, & Saxena, Nitesh (2024). Privacy and Security of Women's Reproductive Health Apps in a Changing Legal Landscape. https://arxiv.org/pdf/2404.05876v1
4. Penny-Dimri, Jahan C., Bachmann, Magdalena, Cooke, William R., Mathewlynn, Sam, Dockree, Samuel, Tolladay, John, Kossen, Jannik, Li, Lin, Gal, Yarin, & Jones, Gabriel Davis (2025). Reducing Large Language Model Safety Risks in Women's Health using Semantic Entropy. https://doi.org/10.1016/j.lanogw.2025.100005
5. Petitti, Diana B., & Chen, Wansu (2008). Statistical adjustment for a measure of healthy lifestyle doesn't yield the truth about hormone therapy. IMS Collections 2008, Vol. 2, 142-152. https://doi.org/10.1214/193940307000000437
6. Zhang, Anru R., & Chen, Kehui (2017). Nonparametric covariance estimation for mixed longitudinal studies, with applications in midlife women's health. https://arxiv.org/pdf/1711.00101v4
7. Gu, Xiangdong, Ma, Yunsheng, & Balasubramanian, Raji (2015). Semiparametric time to event models in the presence of error-prone, self-reported outcomes - With application to the women's health initiative. Annals of Applied Statistics 2015, Vol. 9, No. 2, 714-730. https://doi.org/10.1214/15-AOAS810
8. Liu, Bo, Shi, Shuyang, Wu, Yongshang, Thomas, Daniel, Symul, Laura, Pierson, Emma, & Leskovec, Jure (2018). Predicting pregnancy using large-scale data from a women's health tracking mobile application. https://arxiv.org/pdf/1812.02222v2
9. Gruber, Victoria-Elisabeth, Marinescu, Razvan, Fajardo, Diego, Nassar, Amin H., Arkfeld, Christopher, Ludlow, Alexandria, Patel, Shama, Samaei, Mehrnoosh, Klug, Valerie, Huber, Anna, Gühner, Marcel, Orfila, Albert Botta i, Lagoja, Irene, Tarr, Kimya, Larson, Haleigh, & Howard, Mary Beth (2025). A Women's Health Benchmark for Large Language Models. https://arxiv.org/pdf/2512.17028v1
10. Carillo, Marites F., Largo, Fe F., & Ceballos, Roel F. (2019). Principal Component Analysis on the Philippine Health Data. International Journal of Ecological Economics and Statistics, 39(3), 91-97, 2018. https://arxiv.org/pdf/1902.07905v1