



Mind the Gap: Gender Data and AI Bias

The gender data gap = missing/uneven data about women. As a result, AI decisions skew male through representative, algorithmic, cultural, and intersectional biases.

WHY IT HAPPENS

- Most AI teams are men; design choices reflect their blind spots.
- Training data under-represent women.
- Optimising only for overall accuracy or profit can sideline minorities.
- Women's phone/internet access is lower → fewer data traces.
- Binary labels and averages hides subgroups.

CASES BY BIAS TYPE

Representative

- Face recognition: 35% errors for darker-skinned women (0.8% lighter-skinned men).
- DALL·E 2 job images: women 38% (men 62%); women smiling 2.2× more.
- STEM visuals: 75–100% men.

Algorithmic

- Hiring AI: male-skewed training → women's CVs down-ranked.
- Credit scoring: women fewer/smaller loans despite better repayment.
- Health AI: misses women's symptoms → delayed diagnosis.
- Music recommenders: up to +6.3 pp more accurate for men.

Cultural

- Default female assistants → “women-as-helpers” stereotype.
- Llama-2 stories: women in domestic roles ~4× more; men get higher-status jobs.

Intersectional

- YouTube captions: more errors for women.
- STEM job ads: men ~+20% impressions.
- Book recommenders: less exposure for women authors

CLOSING THE GAP: WHAT TO DO

Representative bias

- Inclusive datasets; document & publish coverage; intersectional benchmarks.

Algorithmic bias

- Remove gender markers from inputs; adjust decision thresholds to balance errors; debias in training and post-processing; continuous monitoring.

Cultural bias

- Neutral/non-binary default voices; design checks for stereotypes; diverse teams in design and testing.

Intersectional bias

- Publish subgroup metrics (gender, skin tone, age, dialect); pre/post-deployment audits; classify HR/finance as high-risk; gender impact statements; transparency standards.

Target audiences: 📖 Librarians, 👩 Professors, 🎓 Students

REFERENCES

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GEDIS project context

This resource is part of the European project GEDIS (Gender Diversity in Information Science), which promotes open educational tools to tackle gender inequalities in higher education, with an emphasis on disciplines related to Information and Library Science. This educational material was developed within the framework of the Summer School Barcelona, as part of the GEDIS project.

GEDIS - Gender Diversity in Information Science: Challenges in Higher Education. <https://ub.edu/gedis>

Citation: Bosshammeer, Svetlana and Daniela Varbanova. 2025. *Mind the Gap: Gender Data and AI Bias*. DOI: <https://doi.org/10.5281/zenodo.17164102>

Co-funded by the European Union. The views and opinions expressed are solely those of the author(s) and do not necessarily reflect those of the European Union or the Spanish Service for the Internationalisation of Education (SEPIE). Neither the EU nor the granting authority can be held responsible.

