g-app

#WhoGetsToSpeak #WhoGetsHeard

WOMEN AT THE TABLE

/thoughtworks

g-app:

Gender Gap App

#Who Gets to Speak #Who Gets Heard:
for democracy + the planet

Measuring representation, participation & influence

Open-source software designed to measure the active participation of women (youth and others) in international events – capturing the **proportion of time, the topics, the capacity and delegated authority of any group whose data is captured speak onstage** or in conference settings.

#Who Gets to Speak #Who Gets Heard on behalf of a changing world in crisis?

At this critical moment in history, we see stark divisions on who helps make the decisions that will affect generations to come. The 2021 **UNFCCC/COP-25 gender report showed 74% of speaking time in plenary was taken by men. The 2022 WHO Executive Board had 91% male Heads of Delegation holding the pen.**

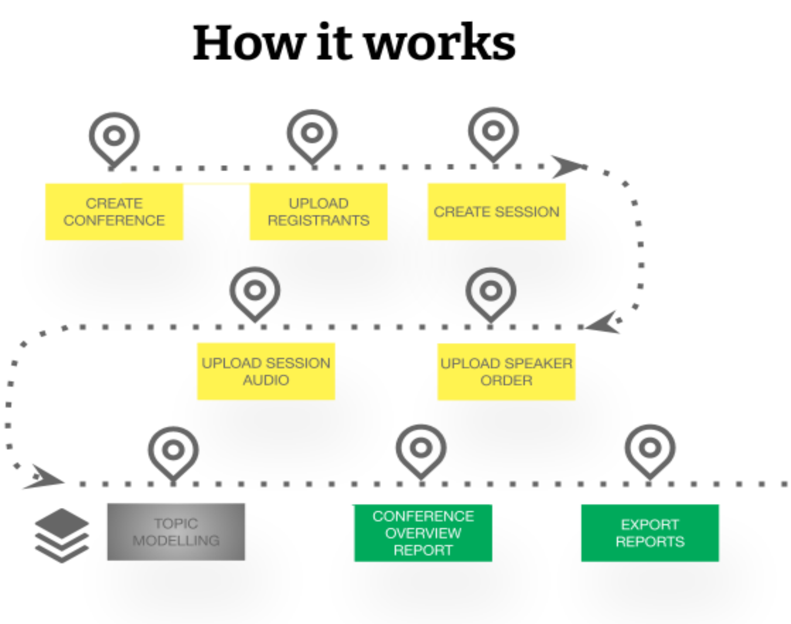
Created by

Women at the Table, along with an 8 person, pro bono, software architecture and development team from **Thoughtworks' Social Impact, India,** and legal support from **Debevoise & Plimpton** for contracts, data protection and Intellectual Property rights have created g-app.

What it does

- Enables **tracking of progress** – what creates successes, or failures, and ways to improve.
- Institutionalises **monitoring** of and **reporting** on representation, participation and influence.
- Analyses **who is speaking, with which authority, and on which topics.**

How it works



What is needed:

- **Excel** with Anonymised Conference **Registrants.**
- **Video recorded file** per panel.
- **Speaker Order.**

Data collection

Software architecture functions by collecting:

- **Topics:** Determined by conference organizers from their official agenda, fed into our algorithm.
- **Conference Demographics**: anonymized conference data (Registration ID, Gender, (Age if tracked) Organisation Type, Country, Conference Role).
- **Video/Audio Recording**: downloaded proceedings per session.
- **Speaker Order: Per session** keyed to anonymized Conference Demographics.

Reports

G-app then automatically **produces graphic reports** on:

- **Gender Distribution**
  - **Percentage** of women (and youth if conference is tracking) **who registered** to the conference **in proportion to how much time they spoke** at the conference.

- Gender (and Youth) **Representation by Region**
  - Broken down by the 5 UN Regions + Total Average

- Gender (and Youth) **Distribution by Conference Roles**
  - Head of Delegation, Delegation, Non-Voting Member

- Gender (and Youth) **Distribution by Session Roles**
  - Chair/Moderator, Keynote/Panelist, Participant

- (**Speaking Time by Age**, if being tracked)
  - Self selected by registrants:
  - <25, 25-35, 35-45.45-55,55-65, >65

- **Speaking Time by Topic**
  - Always with one bar defaulting to Gender, the g-app explainable algorithm uses Topic Modeling to determine who is speaking about which topics.

Results

This data enables g-app to then analyze and graphically represent data on the active participation, representation, and influence of women, regions (and age). It measures: **Who** is at the assembly? Do they have the **power to speak**? Or do they **speak only on certain topics directly related to their demographics**?

1. Gender Distribution

Women & youth who registered to the conference in proportion to how much time they spoke at the conference.

We find registration (representation) often is 60%M - 40%F, but speaking time (active participation) often defaults to 80%M - 20% F. Gender parity via attendance at a conference does not translate into who is speaking and who has influence.

GENDER DISTRIBUTION SUMMARY

Ensuring gender equality in spheres of power, influence and decision-making requires a holistic approach that looks at the institutional environment, decision making processes and the rules of the game.

OUTER CIRCLE REPRESENTS PERCENTAGE OF DELEGATES

INNER CIRCLE REPRESENTS PERCENTAGE OF SPEAKING TIME

DURATION

MEN SPOKE 3 HOURS 30 MINUTES MORE THAN WOMEN OUT OF 9 HOURS 57 MINUTES

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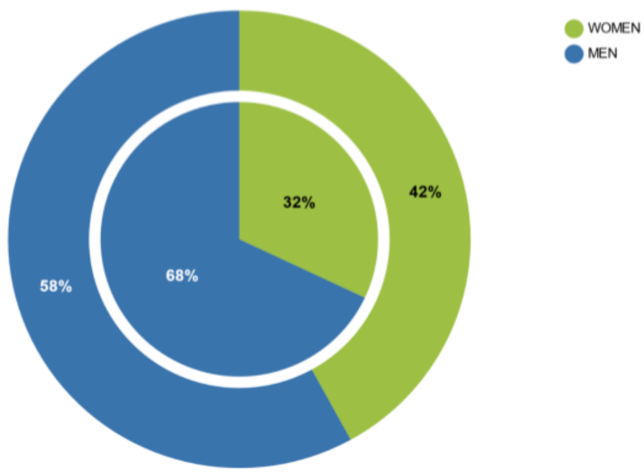


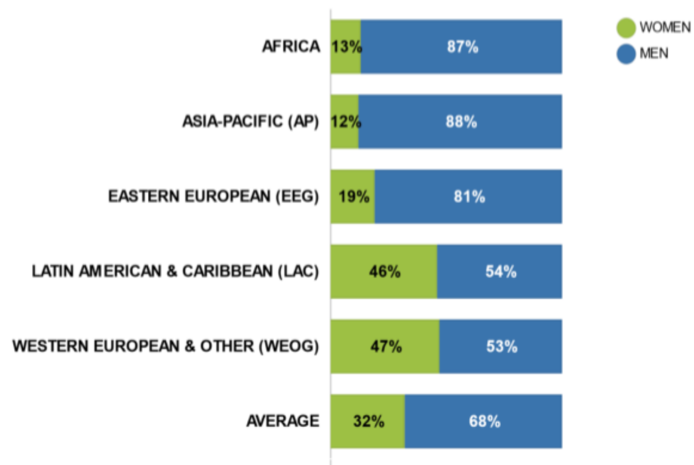
2. Gender Representation by Region.

Keyed to the 5 United Nations geopolitical regional groups, and the average of the conference.

GENDER REPRESENTATION BY REGION

Gender equality objectives are placed high on the international agenda – through conventions such as CEDAW, Women, Peace and Security resolutions of the UN Security Council, and Agenda 2030 for Sustainable Development. These instruments call for action at the national level and set mechanisms for monitoring progress in these areas.

But international decision-making processes still lack similar standards and accountability mechanisms to ensure that women's voices are heard equally and have proper influence.



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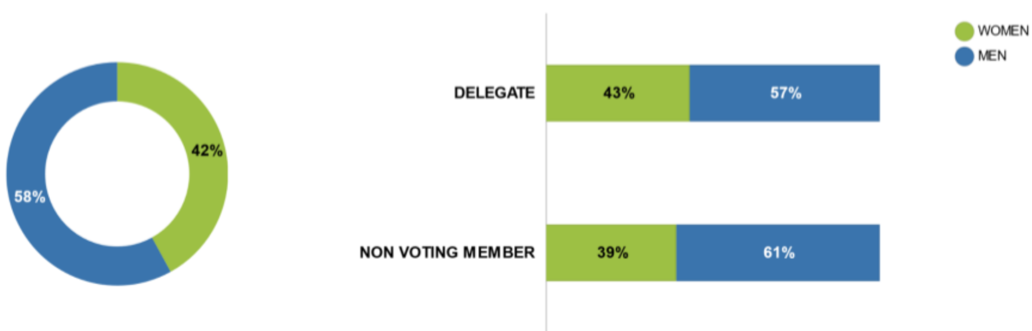
3. Gender Distribution by Conference Roles.

(p.ex, Head of Delegation, Delegate, Non-Voting Member).

We consider conference roles as proxies for influence. The 2022 WHO Executive Board had only 9% female Heads of Delegation (a backwards trend) Consequently, in 2022 91% males made decisions for post-pandemic global health, despite the global health workforce being 70% female.

GENDER DISTRIBUTION BY CONFERENCE ROLES

Assemblies are an important part of the work of any organization, especially those that are international and multilateral in scope. Assemblies set strategic direction and create forums for robust debate and effective agreements.



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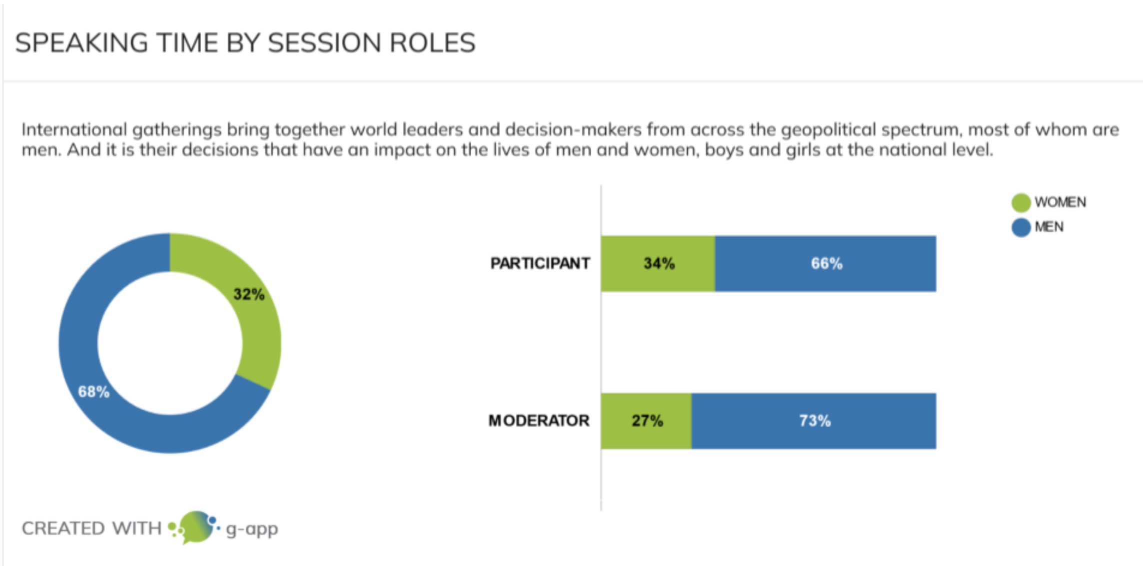
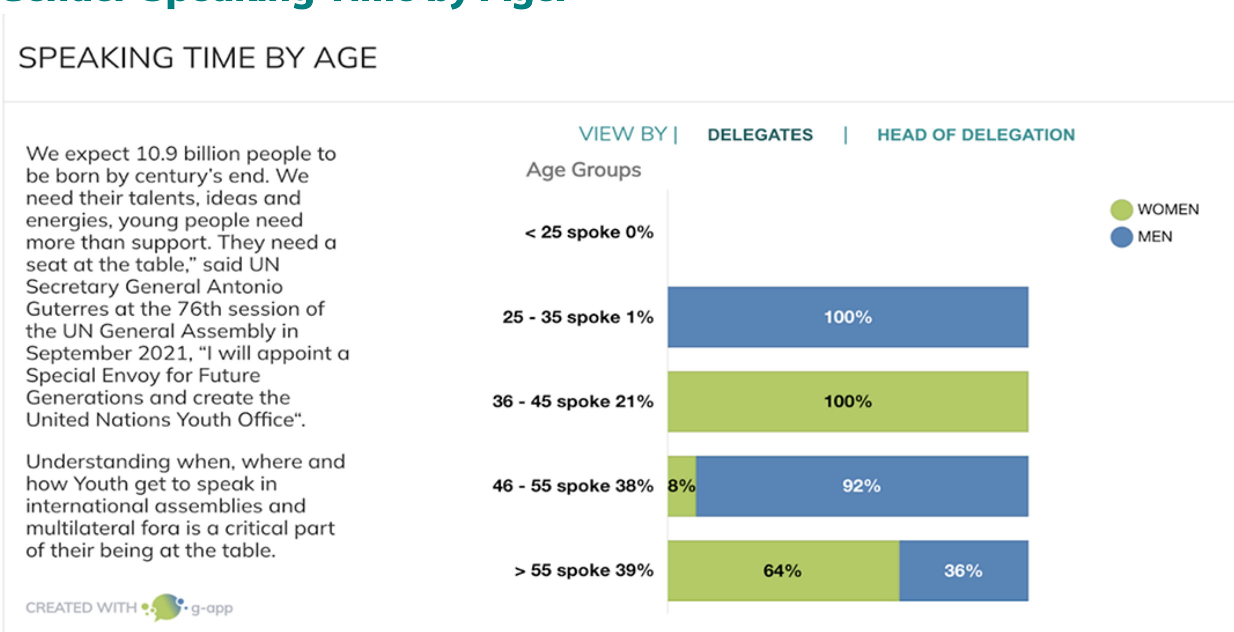
4. Gender Speaking Time by Session Roles

(p.ex, Chair, Panelist, Delegate)

These are other proxies for influence. However these are under the control of the conference organizers (as opposed to delegation composition), and therefore present an opportunity to rebalance proxies of influence with expert speakers.

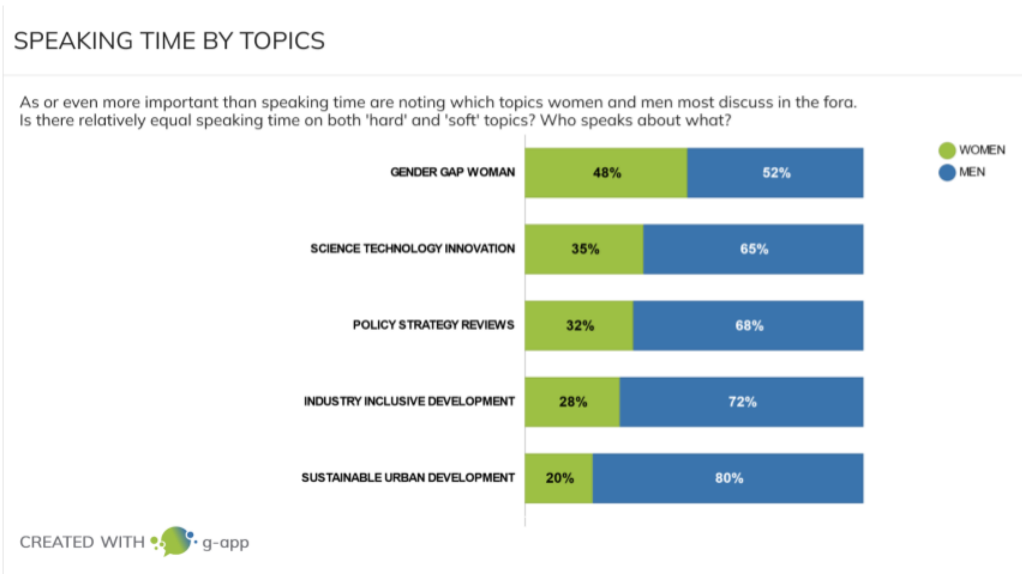


5. Gender Speaking Time by Age.



6. Gender Speaking Time by Topic.

Topics are determined by the conference organizers from their official agenda. The algorithm created for the g-app, uses topic modeling and is also an explainable algorithm part of our work on transparency as well. Who speaks on which topics are of critical importance. Are women speaking as much on gender issues as on cybersecurity or finance? Are youth speaking about labor issues as much as on climate change or education, and on which panels or just in youth streams of discussion?



Statement of Need

Why is g-app necessary?

- **Why is it important to be quantitative regarding 'Who gets to speak & be heard?'** Organizations such as the Inter-Parliamentary Union (IPU), and UN Framework Convention on Climate Change (UNFCCC) have been tracking gender composition as mandated by governing bodies over the last 5-10 years. They have tried to move past counting the numbers of women to counting the influence of women and youth in the conference chamber.

- The g-app was born out of the need to not only capture the numbers of who is attending international events **but to analyse who is speaking, with which authority, and on which topics.**

- It is only optics to have women and youth speak primarily on 'gender and youth' issues and panels. Diverse voices are needed to speak on diverse issues such as climate, the economy, trade and other critical issues affecting us all. With only one set of voices we will never have the breadth and depth of innovative solutions needed to solve our increasingly pressing problems.

- **Data matters.** Being able to collect and visualise what the data means is more effective than stating, "*We need more data…*" or "*We should do better*". Instead the g-app enables tracking progress of what creates successes, or failures, and ways to improve.

- The persistent lack of progress in and the urgent need for improving the representation, participation and influence of women and youth in all aspects of UN processes is vital for achieving the Sustainable Development Goals.

- g-app software premiered at the Paris Peace Forum 2021; was ideated in a Human Centered Design Workshop hosted by Women at the Table in 2019 with teams from the International Union for the Conservation of Nature (IUCN), Inter-parliamentary Union (IPU), World Meteorological Organization (WMO), World Intellectual Property Organization (WIPO), UNAIDS, and UN Women. The software architecture and build was accomplished pro bono in 2021 through Thoughtworks, a global software consultancy traded on NASDAQ and their Social Impact India office, with Debevoise & Plimpton's London and New York offices supplying pro bono legal work on GDPR compliance and Intellectual Property.

- The open source software could be used throughout the UN System and beyond to document and accomplish the aims of true representation, participation and influence in achieving the SDGs. A longitudinal study housed at University College Dublin is also planned for the trove of anonymised data beginning either at COP-27 or in early 2023.

Explainability in machine learning projects

The use of algorithms to automate or delegate decision making processes is increasing and can be found in a diverse range of domains. Sometimes this is driven by a desire to cut costs; occasionally it comes from a belief that algorithms are more "objective" and "unbiased" when it comes to decision-making. This belief is false; algorithms are only as good and fair as the data used to train them and the cost functions they were taught to optimize.

As we increasingly delegate important tasks to machines, it's important to remain sensitive to what algorithms can and cannot do. This is particularly crucial when they are used to make crucial decisions that could seriously affect the lives of many people. If we create a learning algorithm that tries to blindly copy historic data, it's highly likely that algorithms will replicate the biases and unjust practices of the environment from which the data emerged.

What can we do practically to avoid these issues? How can a team of Data science or machine learning engineers, maybe with limited data and domain knowledge, make sure this is avoided?

There are multiple aspects to creating a fair model:

- **Data**: Make sure the sample data is an accurate representation of the population. In cases where the actual population itself is biased due to pre-existing unfair practices, consider altering the data/sampling technique to remove the bias. For example, if you are trying to automate hiring processes, if the actual population of people hired historically is biased, then the data needs to be altered to avoid transferring this bias into the new automated hiring system.
- **Problem formulatio**n: Make sure the mathematical problem statement being solved matches the actual business problem and not an unfair or inaccurate proxy of it. A good example of this is IMPACT, a teacher assessment tool developed in 2007 in Washington, D.C. It was supposed to use data to weed out low-performing teachers. But 'low-performing' was initially defined by the grades of the students taught by these teachers. This led to many unfair instances of good teachers of students with special educational needs being fired.
- **Explainability**: Even if a model is created with due consideration to the two aspects above, stakeholders and consumers can verify if the model is robust and unbiased only if it is explainable — in other words, only if they understand it can accountability be established and clarified.

Although all three are important, the final point - explainability - is often overlooked. One of the reasons for this is that it is the most challenging as it places additional demands on people using algorithms. This article focuses on explainability; first it provides a brief recap before then exploring how we can incorporate explainability into a machine learning model.

Learn more about **EXPLAINABILITY** in [this article] written by our partners from ThoughtWorks.