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MAPPING DEMOCRACY-AFFIRMING TECHNOLOGIES WORLDWIDE

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Democracy-affirming technologies hold immense potential for bolstering democratic values and processes, but these technologies may not prioritize democratic values by design. This paper addresses the misalignment between the democratic use cases of Tech4Democracy startups and the actual design of their technologies and explores the implications for democratic values and participation. Drawing on a methodology that combines a Tech Radar approach and NLP analysis of a worldwide patents database, this analysis investigates the current landscape of democracy-affirming technologies based on a Global Entrepreneurship Challenge organized by IE University (Center for the Governance of Change & Center for Entrepreneurship and Innovation) in partnership with the U.S. Department of State and with the strategic support of Microsoft. The analysis reveals such risks associated with the lack of democratic intentionality in technology design as unexpected biases, exclusionary practices, and public distrust.

INTRODUCTION

“Ethics by Design” is an approach advocated by the European Commission to address ethical issues in AI development. It emphasizes the proactive integration of ethical principles as system requirements during the development stage. The goal is to prevent ethical issues from arising in the first place rather than attempting to fix them after the system’s deployment. This “Ethics by Design” framework nevertheless recognizes that some ethical concerns may only become apparent during development and others post-deployment. The principles are used as guidelines to steer the design process, and ethical requirements may extend to not only the AI system, but also the development processes.[1]

A similar logic could be applied to democracy-affirming technologies. Just as “Ethics by Design” seeks to embed ethical considerations into AI systems, democracy-affirming technologies can be democratic by design. In other words, principles and requirements that support democratic values and processes should be incorporated into the development of these technologies. By incorporating democratic values like transparency, citizen engagement, and inclusivity into the core system requirements, we improve the potential to preemptively address or lessen democratic challenges that may surface during the implementation or utilization of these technologies.

In this report, we explore the conceptual contrast between two distinct areas of technology as it intersects with democratic systems: "tech for democracy" and "democracy-affirming technologies".

On the one hand, "tech for democracy" here refers to technology products that are applied to democracy-related use cases, e.g., digital tools for organizing political campaigns, platforms for civic engagement, and systems for online voting. On the other hand, "democracy-affirming technologies" is a term defined by Blázquez-Navarro in the foreword of this report. These technologies are designed, developed, and deployed with a specific purpose in mind: to foster core democratic values, principles, and rights throughout their lifespan. Among the core values, principles, and rights that these technologies aim to support are personal liberty and autonomy, privacy, data protection, inclusion, access to truthful information, the promotion of critical thinking around technology, the enablement of technologically savvy legislative bodies, the participation in free elections, the separation of powers, the principle of legality, and the rule of law.

Our objective in this report is to use an international sample from the startup ecosystem to show how this sector is using existing technologies to build applications that support democracy. Our research reveals that there is no deliberate effort to create democracy-affirming technologies per se, and this observation prompts us to consider a wide range of interpretations about the potential risks and opportunities that come with the ongoing development and establishment of democracy-affirming technologies.

METHODOLOGY

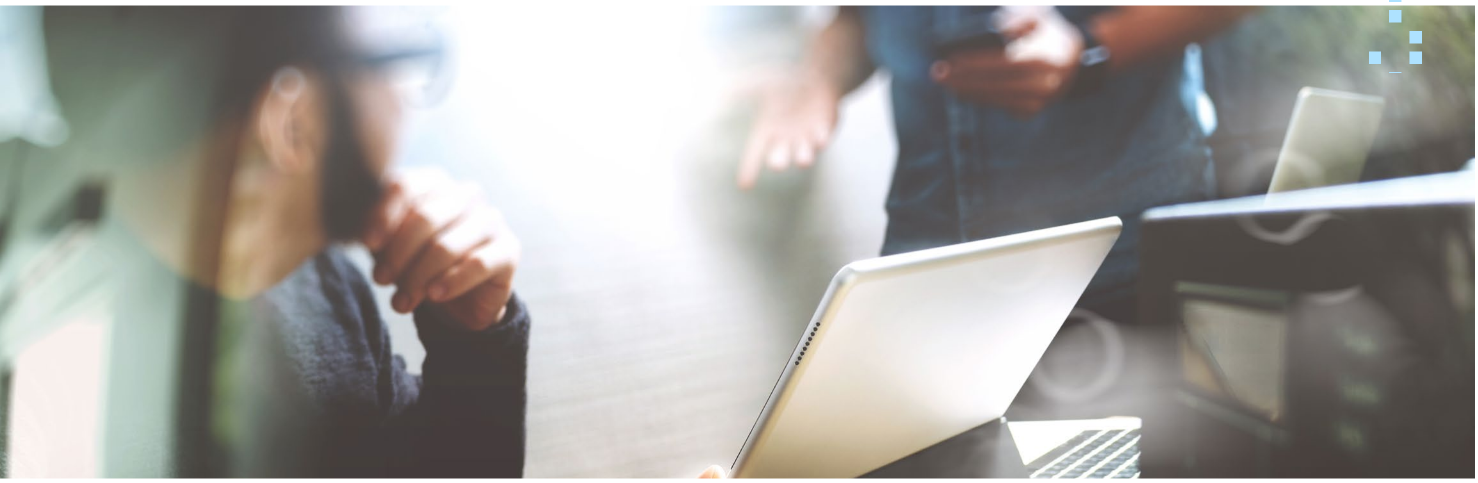
Sampling: A worldwide startup competition

IE University hosted tech startups competitions in five continents: Europe (at IE University in Madrid), South America (at Universidad de los Andes in Bogotá), North America (at Stanford University in Silicon Valley), Asia-Pacific (with ORF in conjunction with the Raisina Dialogue during the G20 in New Delhi), and Africa (at the University of Cape Town). The five continental winners competed in a Global Final in Washington, D.C.

More than 300 startups from 68 countries applied to be part of one of the six competitions of Tech4Democracy's Global Entrepreneurship Challenge. Indeed, startups all around the world were contacted by IE University's Center for Entrepreneurship and Innovation, either directly or through databases, associations, and networks, to inform them about the open calls and encourage them to apply.

For every one of the six challenges, an online semifinal was held for between 9 and 11 selected organizations to select between three and six finalists for each in-person event.

At both the semifinals and the finals, each competitor had five minutes to pitch their solution, and then a panel of judges had five additional minutes to ask questions of each competitor.



The evaluation criteria for both the semifinal and the final (below) were all weighted equally:

- **Contribution to democracy:** To what extent does the organization's technological solution have the potential to contribute to the defense and promotion of liberal democracy as a political system and of democratic values such as liberty, equity, inclusion, privacy, freedom of expression, access to information, transparency or fairness?
- **Technological innovation:** To what extent does the organization's solution leverage digital or other technologies that are relatively new/uncommon or are used in relatively new/uncommon ways?
- **Viability/scalability:** To what extent is the organization's technological solution commercially viable (if it is still in its development phase) or scalable (if it has already been commercialized)?
- **Interest for investors:** To what extent is the organization's technological solution interesting for investors due to its potential profitability?
- **Team:** To what extent does the organization count with an excellent leadership team and staff? Taking into account experience, knowledge, skills, and diversity.

This study uses a sample of 53 semifinalist startups to extrapolate about the current landscape of technology-affirming startups, with a focus on their origin, area of focus, the gender of the founder, and the maturity of their technology.

We acknowledge that this methodological approach presents certain limitations. It does not necessarily represent the entire sector but rather those who self-selected by participating in Tech4Democracy and were subsequently chosen as semifinalists. What is more, the 53 semifinalists were selected by IE University within a startup competition that the same institution organized, so the sample is biased toward the scope of our outreach and our selection criteria. The process of categorization is inevitably somewhat artificial.

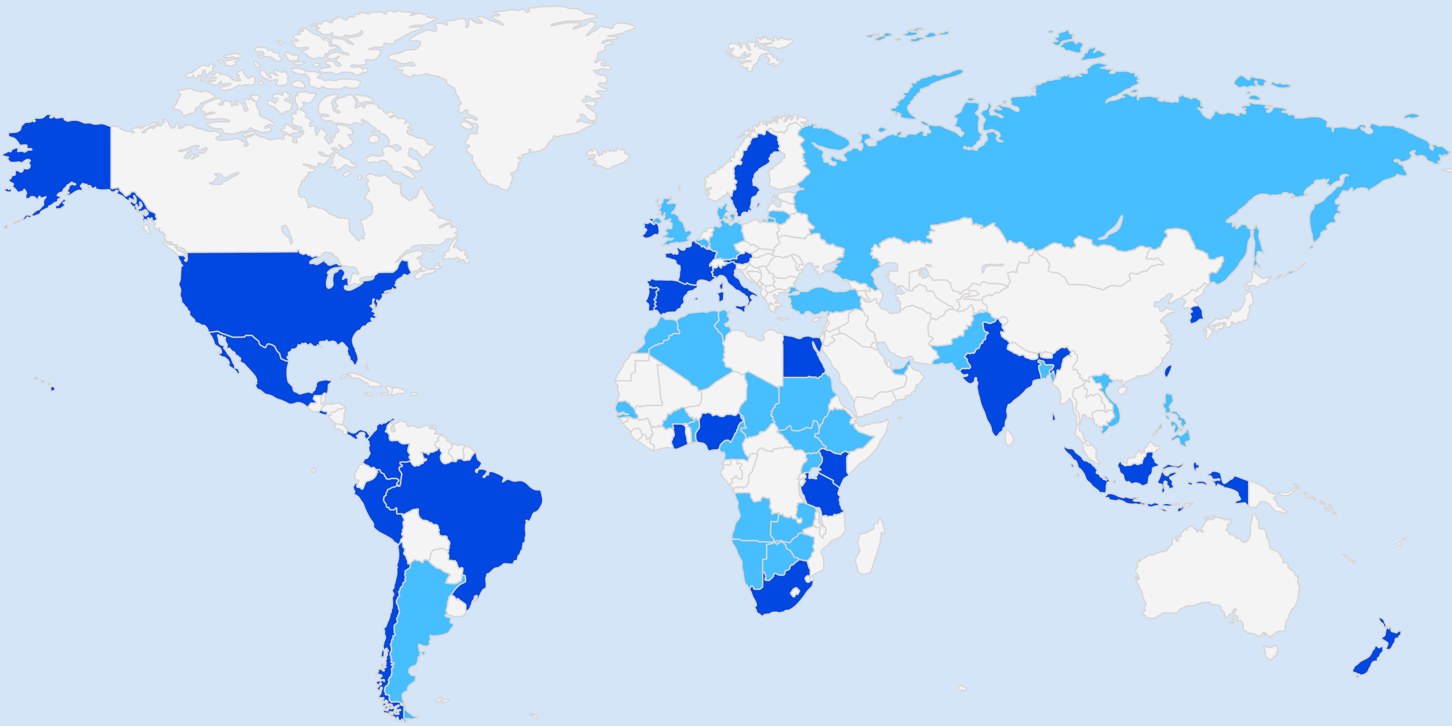
We aimed to develop a methodology that would be both appropriate and innovative for our purposes informed by these limitations imposed by the sample size, data availability, and the rapidly changing landscape of the intersection of society and technology. This investigation did not yield a comprehensive body of scientific evidence, but it illuminates potential opportunities and insights for industry stakeholders to further enhance the democratic implications of their technological applications.

This initial venture into uncharted territory seeks to be groundbreaking in terms of not only content and its visibility within the confluence of society and technology, but also methodology. Despite the acknowledged constraints, we have striven to pioneer a methodology that balances rigor with the necessity for swift understanding in a fast-paced and evolving field. The preliminary outcomes from this effort underline the importance of continuing this line of inquiry.

300 organizations from **68** countries applied to compete in the Global Entrepreneurship Challenge.

53 semifinalists were selected from that sample, representing **29** countries.

Map 1: Countries represented in the Global Entrepreneurship Challenge. Dark blue indicates startups that reached the semifinal, whereas light blue indicates countries where the startups that competed did not reach the semifinal.



Distribution by area of focus

Our Global Entrepreneurship Challenge identified ten areas of innovation where democracy-affirming tech organizations are making an impact. The areas, listed from the most to the least represented in our sample, are:

- **CivTech (12 startups):** Digital platforms that leverage technology to facilitate, promote, and enhance citizen engagement in policymaking (through expressing opinions, voting on alternatives, proposing solutions, etc.) and/or connection, interaction, and collaboration between citizens and policymakers.
- **Equity and inclusion (9 startups):** Organizations that use technology to defend and promote social equity and inclusion of women, economically disadvantaged groups, people with disabilities, and underprivileged groups in general.
- **Enhanced social networking (8 startups):** Digital platforms that allow for a better social networking experience by decentralizing control of the network through web3 technologies or introducing moderation and other tools to foster a healthier civic conversation and combat polarization, fake news, and hate speech.
- **Data for policymaking (6 startups):** Technologies that deliver better data collection, processing, and visualization to inform policy- and decision-making processes in a way that is respectful of privacy and individual rights.
- **Digital identity and trust (5 startups):** Transparency technologies and identity recognition or protection technologies that ensure inclusive access to digital public services and protection of sensible data.

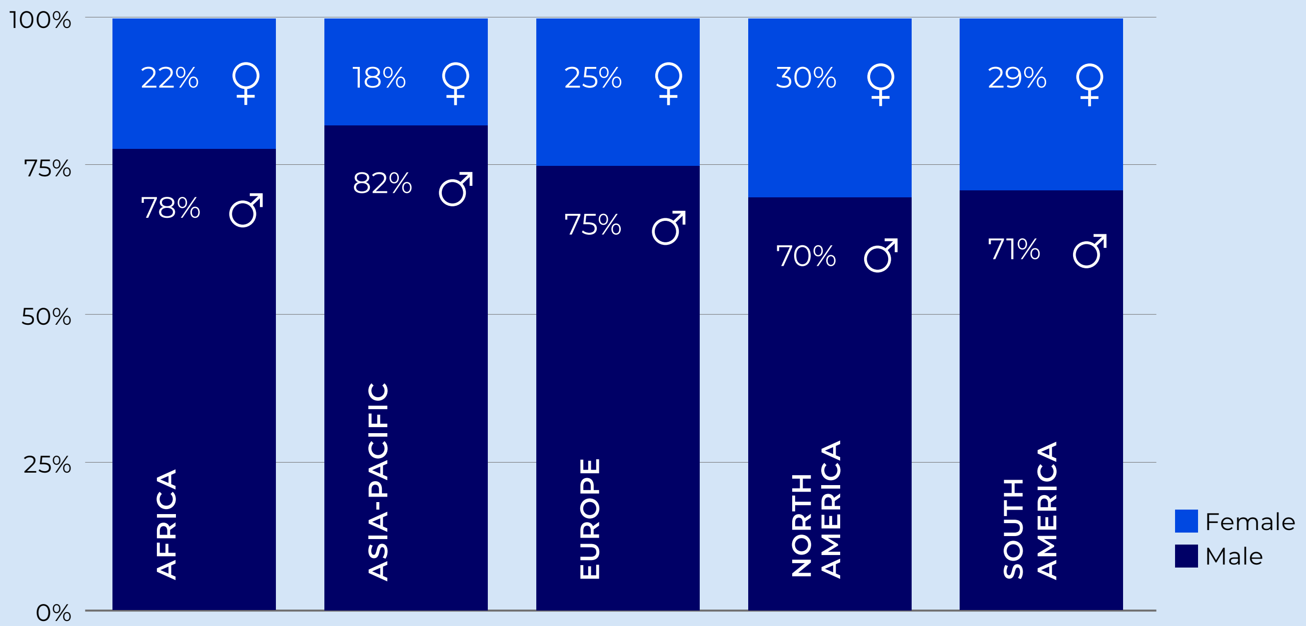
- **Tools to fight disinformation (3 startups):** Technologies that support fact-checking efforts, identify bot activity, or work on social data to promote accurate information on key matters, including electoral processes.
- **GovTech (3 startups):** Organizations that apply digital technologies to improve, modernize, and optimize government services, operations, and administration–notably with a focus on public procurement processes.
- **E-voting (3 startups):** Startups that allow for the organization of secure digital electoral processes, often through the use of encryption, and facilitate voting.
- **Campaigning (3 startups):** Digital solutions to organize large campaigns (either political campaigns for public office and/or campaigns for social change) with tools that facilitate public outreach, supporters' engagement, data management data, etc.
- **Responsible AI (1 startup):** Automated decision-making systems that provide equal opportunity, do not discriminate and are fair, explainable, auditable, ethical, and accurate.

Distribution by gender of founder

The gender distribution among startup founders varies significantly across different regions. The gender distribution is the most balanced among the North American participants, with 70% of startup founders being male and 30% female. This region is leading the way in gender parity among startup founders. In contrast, the Asia-Pacific region has the least gender balance, with 82% of startup founders being male and only 18% female.

This disparity highlights the need for more initiatives to support and encourage female entrepreneurship in the Asia-Pacific region. This inequality is reflected compare these figures with global data. According to the Global Entrepreneurship Monitor (GEM) 2021/2022 report, startup rates for women dropped by 15% from 2019 to 2020.[2] Another study indicates that men still outnumber women 3-1 among business owners.[3]

Figure 1: Distribution of gender of founder per continent



Building a tech radar through an NLP analysis of a patent database

A tech radar visualizes the varying applications and maturity levels of different technologies. Our aim was to ascertain which types of technologies are being employed in the four major areas of innovation boasting the highest volume of startups: civtech, enhanced social networking, data for policymaking, and equity and inclusion. We selected 16 technologies or interfaces extensively used in the industry: Analytics, Augmented Reality (AR), Big data or LLM integration, Biometrics, Chatbot, Cloud, Cybersecurity, Distributed Ledger Technology (blockchain, cryptography), Machine Learning, Natural Language Processing (NLP), Open-Source Software, Predictive Analytics, Quantum computing, Social Media interface, Virtual Reality (VR), and Web or mobile interface.

Our research methodology was built around a systematic Boolean query search of the World Intellectual Property Organization (WIPO) database, a data set selected for its comprehensiveness, inclusivity of worldwide patents, and its integrated translation functionality. WIPO's database, PATENTSCOPE, ensures immediate access to published International PCT applications in full-text on the day of publication.[4]

A unique query was formulated for each of the 16 technologies that used Boolean operators to include all patents meeting the specified criteria and exclude those unrelated to the technology under scrutiny. WIPO's automatic translation tool, WIPO Translate, enabled the inclusion of patents filed in languages other than English and supported a thorough, global overview of the patent landscape for each technology.

Technology maturity can be quantified in many ways (e.g., market size, investment, momentum in conversations), and we chose to classify technologies based on the number of global patents. The reasons for this classification were two-fold:

(a) it enabled a systematic methodology applicable to all technology branches; and

(b) measuring the number of patents curbed the bubble effect, which could inflate results if other values (e.g., capital or user base) were measured.

A potential risk of using patent count as a proxy would be a tautological fallacy: technologies that rely on Open-Source code would not be considered as mature as they actually are because, by nature, they have fewer patents. Another potential limitation of this approach would be overlooking actual usage in regions with diverse intellectual property regimes or in rapidly advancing sectors like artificial intelligence and quantum computing.

To augment the robustness of our methodology, we recommend that future research integrates such additional metrics as market size, investment volume, momentum in academic and industry discourse, user base size, and sentiment analysis. Moreover, we propose a shift from an exclusive focus on absolute volumes to an analysis of trends to provide critical insights into the technologies that are gaining momentum.

We found some technologies with a much higher number of patents: social media interface (6,001,553), web or mobile interface (2,817,524), and predictive analytics (2,222,429). The technology branches with markedly fewer patents were natural language processing (16,336), conversational AI (29,503), and quantum computing (40,101).

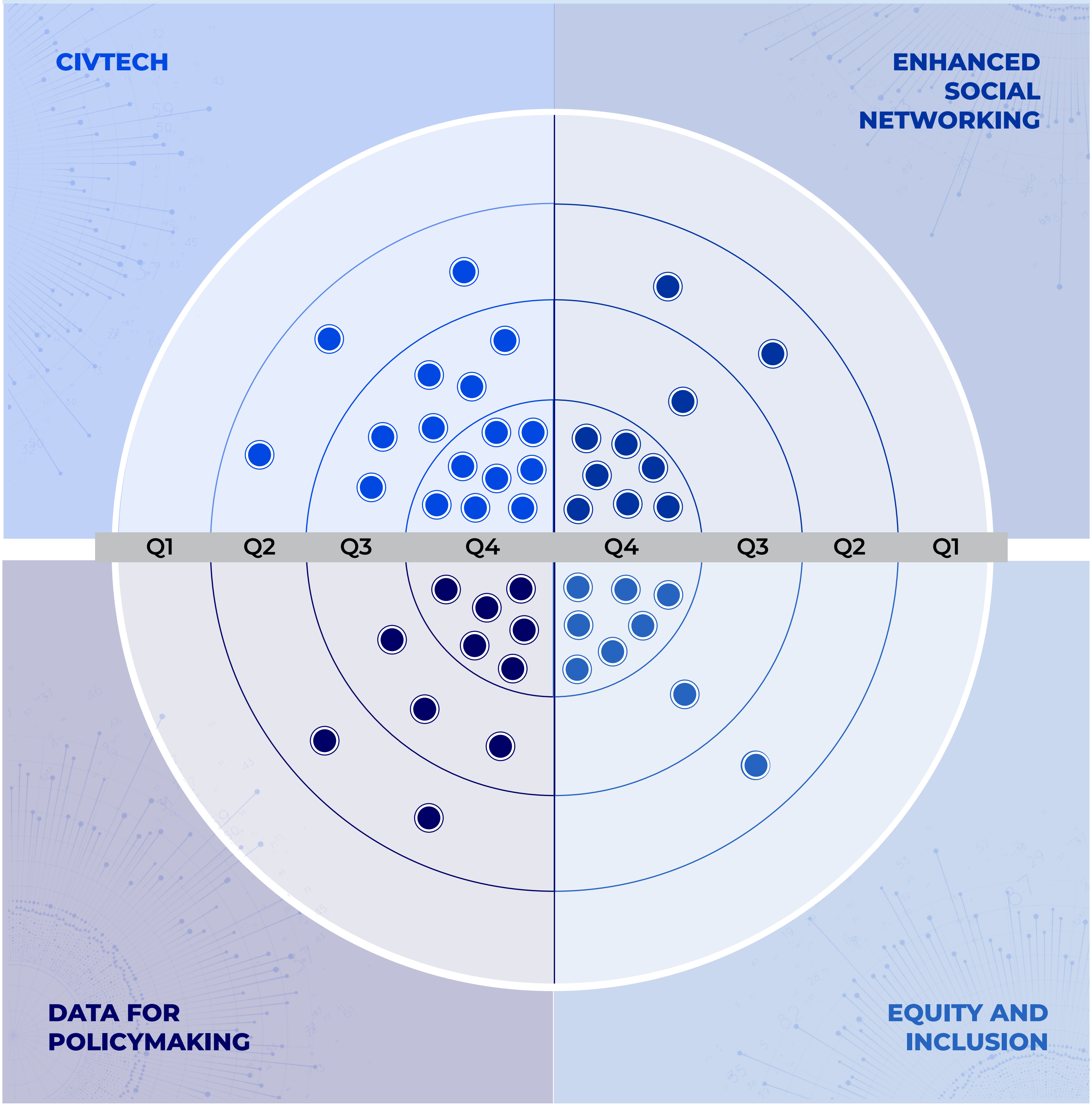
We used the interquartile range (IQR) method to define quartiles for the patent count data, calculating the range between the 25th and 75th percentiles of the sorted data. The patent counts at the 25th, 50th, and 75th percentiles determined the ranges for Q1 (between the 3rd and 4th patent counts, approx. 2,079,967), Q2 (between the 8th and 9th patent counts, approx. 711,112), and Q3 (between the 12th and 13th patent counts, approx. 264,976).

Finally, we classified the participating startups not only by their area of innovation but also by the technologies they employ. Some utilize several. Each technological application of a startup represents a data point, or what ThoughtWorks, the consultancy that devised the tech radar, call a "blip". We modified the quadrant and ring terminologies utilized in the ThoughtWorks template to better fit our working framework.

RESULTS

A visual inspection of the constructed tech radar makes clear that none of the companies included in this study are implementing technologies from the first interquartile range with the least number of patents, namely natural language processing (16,336 patents), chatbot (29,503 patents), quantum computing (40,101 patents), and distributed ledger (156,013 patents). The heart of the radar is densely populated with technologies exhibiting a high volume of patents. The most adopted technologies among the surveyed companies include social media interface with a staggering 6,001,553 patents, followed by web or mobile interface (2,817,524 patents), predictive analytics (2,222,429 patents), and augmented reality (1,937,504 patents).

Tech Radar: Each quadrant represents one of the four most common areas of innovation within the Tech4Democracy Challenge. Each blip represents the technologies used by those companies.
The rings represent the interquartile intervals: Q1 comprises the technologies with least patents and Q4 the technologies with most patents.



DISCUSSION

The results derived from the technological radar suggest that the companies within our sample are utilizing mature technologies and customizing them for the democracy-related industry. They seem to be building their value proposition on the creation of web or mobile interfaces that are user-friendly for various buyer/user personas within this sector (e.g., public institutions, citizens or officials). These entities also appear to be developing business models tailored to meet the consumption requirements of their respective clientele. For a comprehensive comparative analysis, an analogous tech radar assessment across various technology sectors is essential. This approach will enable us to ascertain whether the adoption rate of mature technologies in the field of democracy-affirming technology is above or below the average. For example, the adoption of machine learning is on the rise in fintech. Nearly 90% of companies anticipate an increase in their utilization of machine learning in the forthcoming 12 months, with a significant 45% forecasting a substantial surge.[5]

What are the risks associated with these results?

A misalignment can arise between the goals of commercial technologies and those of democracy-affirming technologies. This misalignment is exacerbated when Tech4Democracy startups repurpose commercial technologies for democratic use cases. The implications of this misalignment could be significant, particularly in terms of inclusion and engagement.

Inclusion is a critical aspect to consider when designing software for the democracy sector. Moyo (2022) discusses long-standing quality practices in software development, including the importance of designing high-quality software development methods that promote inclusion.[6] This approach is consistent with the need to consider all different use cases and potential excluded groups when designing software for the democracy sector. For instance, when designing a voting app, developers should consider the needs of various user groups, including those with disabilities. This could mean incorporating features like text-to-speech for visually impaired users or simplified user interfaces for elderly users who may not be as tech-savvy.

Something that bureaucracy and coding have in common are protocols. If protocols are designed to support diversity, then the result of the protocol will be inclusive toward the diverse group. For example, a protocol in a government service portal could be designed to provide information in multiple languages, thereby ensuring that non-native speakers are not excluded from access to important services. It is, however, important to note that bias is unavoidable in software design. The creator of the model chooses the criteria for inclusion when conceptualizing, building, and training it. A user may not even be aware of the bias generated and the criteria to fix it that exist.

To underscore the significance of this limitation, let us revisit the earlier example of a voting app designed with inclusivity in mind. Despite the developers' meticulous efforts to make the app accessible for visually impaired users, they may inadvertently overlook certain types of visual impairments. This could result in a product that, while inclusive for some, still exclude others. Tiago Guerreiro's PhD thesis provides a compelling exploration of this issue. Guerreiro conducted a comparative study of how individuals with varying degrees of sight interact with the same app. His findings revealed substantial differences in usability experiences among the participants and underscored the complexity of designing truly inclusive technology UX/UI.[7] This highlights the need for comprehensive protocols in technology design that ensure that all potential user groups are considered during the development process and minimize the risk of unintentional exclusion. Within this same report, Trisha Ray further develops this idea.

Toussaint et al. (2022) discuss the propagation of bias through design choices in on-device machine learning workflows for AI/ML models. They highlight that design choices during model training, like the sample rate and input feature type, a nd optimization, like light-weight architectures, the pruning learning rate, and pruning sparsity, can result in disparate predictive performance across different groups.[8] This underscores the importance of being aware of potential biases and taking steps to mitigate them in the design process. This is not possible when adopting external models.

Social network models have gained traction in the Tech4Democracy sector, where they are being applied to enhance communication between citizens and between citizens and their governments. Many cities and citizen collectives are implementing social network models, however, social networks thrive on the engagement economy and assign criteria to their information sorting algorithms to privilege content that can generate more engagement and clicks.[9] Potential deployers of these citizen social networks must question the trade-off: implement their processes of citizen "social networking" on existing platforms and take advantage of their network effect (more users lead to more users), or opt for the creation of unique social network platforms using algorithms that may be more democracy-oriented by design.

The tech radar discussed here presents a series of questions that surpass available answers. Two primary inquiries arise: why does this situation occur, and how can it be enhanced?

The question of market size is particularly pertinent. The development of such transformative technologies as generative AI, blockchain, quantum computing, and conversational AI is often constrained by significant costs and risk factors. The market for these technologies, particularly within the context of democracy-affirming applications, might not be sufficiently mature or expansive to attract enough funding and resources to stimulate and expedite development. Without adequate financial incentives, the evolution and integration of these technologies within the democratic framework may be hindered.

Regulation, particularly in the realm of sensitive data handling, is a crucial balancing act. While these frameworks aim to protect individual rights and uphold ethical standards, they can inadvertently constrain technological innovation. For example, strict data protection regulations, as necessary as they are, may limit the full utilization of AI in areas like opinion analysis and predictive policymaking. This observation is not a critique of regulation, but a call for its evolution and foster a dialogue that results in adaptive regulations that not only respect privacy and individual rights, but also enable technological progress. This balance will require active engagement from all stakeholders, including policymakers, technologists, and society at large. Through collective effort, we can cultivate an environment where both democratic values and technological innovation can thrive.

CONCLUSION

Democracy-affirming technologies might not be democratic by design. The data obtained from the Tech4Democracy startup competition highlights the risks and challenges faced in creating democracy-affirming technologies. Biases, exclusions, and the erosion of public trust are among the primary concerns when democratic intentionality is overlooked.

To address these issues and promote the democratization of AI, a multi-faceted approach is required. Collaborative efforts between policymakers, technologists, and researchers are essential to embed democratic principles into technology design processes. By mapping AI development and focusing on areas where democratic technologies are most needed, we can foster inclusive and participatory governance, civic engagement, and social justice.

The fact that companies are mostly aiming for quick wins by implementing easily applicable technologies to resolve issues related to democracies offers the advantage of quick turnarounds and leveraging proven, mature technologies. However, the temptation to borrow directly from solutions effective in other domains such as fintech or healthtech should be approached with caution. The core reason being that these tools may carry inherent biases or blind spots that may not be immediately apparent when shifted into a new context. Given that democracies are multifaceted and complex, the potential for unintentional exclusions and bias is considerable. Companies should, therefore, commit to rigorous due diligence when using open-source or already consolidated technologies. In particular, they need to consider potential biases and assess their impact on the specific application.

However, it's worth noting that the sole reliance on adapting existing tools may fall short of addressing the unique challenges inherent in democratic systems. The need for technologies that are specifically designed with democratic principles from the outset, or what we term as "Democracy by Design," becomes clear in this context. The complexity and scale of such an endeavor, however, might be beyond the capacities of startups acting in isolation. Therefore, we propose a collaborative approach.

To successfully achieve this, the formation of strategic alliances and partnerships between governments, large tech firms, startups, and citizen initiatives becomes essential. This collaborative approach allows for the pooling of resources, varied expertise, and diverse perspectives, which would significantly increase the likelihood of developing solutions that embody a comprehensive understanding of the democratic context. Such partnerships not only foster the development of advanced technologies but also ensure these tools are designed with a keen understanding of the democratic context in which they will operate. Furthermore, these collaborations can pave the way for industry-wide standards and benchmarks, driving greater alignment of the sector with democratic principles. As a result, this sector could transition from merely applying innovations developed in other sectors towards fostering a new generation of democracy-affirming technologies.

Continued research is crucial to further explore innovative strategies that align technology with democratic values. By actively monitoring AI projects and infusing democratic principles at their core, we can create a future where technology empowers citizens and promotes social equity.

ENDNOTES

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