Perspective

Intersectional analysis for science and technology

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Intersectionality describes interdependent systems of inequality related to sex, gender, race, age, class and other socio-political dimensions. By focusing on the compounded effects of social categories, intersectional analysis can enhance the accuracy and experimental efficiency of science. Here we extend intersectional approaches that were predominantly developed in the humanities, social sciences and public health to the fields of natural science and technology, where this type of analysis is less established. Informed by diverse global and disciplinary examples—from enhancing facial recognition for diverse user bases to mitigating the disproportionate impact of climate change on marginalized populations—we extract methods to demonstrate how quantitative intersectional analysis functions throughout the research process, from strategic considerations for establishing research priorities to formulating research questions, collecting and analysing data and interpreting results. Our goal is to offer a set of guidelines for researchers, peer-reviewed journals and funding agencies that facilitate systematic integration of intersectional analysis into relevant domains of science and technology. Precision in research best guides effective social and environmental policy aimed at achieving global equity and sustainability.

Intersectional approaches emerged in the 1950s to 1970s from the US civil rights and feminist movements[1,2]. In 1989, the legal scholar Kimberlé Crenshaw coined the term intersectionality to describe how multiple forms of discrimination, power and privilege intersect in Black women's lives, and how their specific intersectional experiences are erased when sexism and racism are treated separately[3,4]. Historically, scholars in the humanities and social sciences (including law) developed intersectionality primarily based on qualitative research[3,5–8]. Since then, quantitative intersectional approaches have emerged across diverse fields such as psychology, political science, labour economics and public health[9–12]. Pressing technological developments and environmental challenges make it critical to extend intersectional approaches to technology and the natural sciences (Box 1).

Emerging artificial intelligence (AI) technologies are transforming our interactions with both the digital and physical worlds[13–16]. The importance of taking an intersectional approach is best illustrated through the iconic example of facial recognition used in security systems and personal devices such as smartphones. Evaluating bias in three commercial services for facial recognition, researchers detected an intersectional disparity in algorithmic performance, with much higher error rates for darker-skinned women (ranging from 20.8% to 34.7%) compared with lighter-skinned men (ranging from 0% to 0.8%), lighter-skinned women (ranging from 1.7% to 9.8%) and darker-skinned men (ranging from 0.7% to 12.0%)[17]. In the wake of these findings, large technology companies released new AI models with increased accuracy across gender categories and skin phenotypes. However, the Saving Face audit, which covered additional factors, such as a person's age, revealed a critical issue. While optimizing for fairness on gender and skin tone, these adjustments compromised fairness across age categories, with models showing markedly poorer performance in classifying the age of dark-skinned women compared with other demographic groups[18]. Without integrating an intersectional analysis of how AI-based technologies are developed and their outputs are interpreted, we risk intensifying existing inequalities[19–21]. Research shows that algorithmic utility and fairness require ongoing monitoring and iterative refinement[22].

Similarly, global warming poses an existential threat to humans and planetary health[23–28]. Here again we see the importance of intersectional analysis. Research from South Africa shows that households headed by women, especially those led by Black African women, are the most

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Box 1

Intersectionality

Intersectionality defines interconnected socio-political dimensions such as race, class, gender, age, educational status or migration status as they function within interdependent contextual domains and environmental conditions linked to systems of power, privilege and oppression. Although not relevant to all research, intersectional analysis is often central to studies that address questions with direct or indirect human implications. National and international policy bodies and research councils, including the European Commission[170], the Science Granting Councils Initiative in Sub-Saharan Africa[162] and the World Health Organization[171], increasingly advocate for intersectional research, where relevant, to address global challenges. United Nations Women, for example, emphasize that "failure to address complex social systems and identities can obscure or deny the human rights protections due to all"[172]. The US Office of Human Services policy seeks to embed "an equity and intersectionality framework in research" to advance "people's well-being through research, evaluation, and analysis activities"[173].

Box 2

Intersectional factors may be considered at three levels of analysis

Socio-political dimensions refer to the social categories, identity variables and positions of advantage and disadvantage, including sex, gender, ethnicity, sexual orientation, class, caste and religion, that may be central to intersectional analysis. 'Dimensions' captures the idea that each category may include multiple sub-variables.

Contextual domains refer to large social systems, such as legal, healthcare or criminal justice systems, state or global policies, educational institutions and religious bodies, that contribute to social advantages or disadvantages at the socio-political level. These domains may shape individual life choices and opportunities, and should be considered in any intersectional endeavour.

Environmental conditions refer to local and global dynamics related to air, soil and water quality, for example. Capturing positions of privilege and disadvantage in the domain of environmental conditions requires attention to community-level variations to identify who is at risk from environmental hazards and climate-related disasters, and who is most likely to be protected and resilient[174].

vulnerable to energy poverty (lack of sufficient, affordable and sustainable energy services). Adding geographic location to the analysis reveals that energy poverty is particularly pronounced for these households in rural areas, with significant consequences. When energy fails, girls are likely to be withdrawn from school to collect fuel for cooking, thereby risking life-long illiteracy[29]. An analysis focusing solely on gender or race would miss these layered vulnerabilities. By contrast, the intersectional approach highlights the value of considering the interdependent dynamics of race, ethnicity, gender and geographic location to identify those who are most at risk and to guide mitigation strategies. In this space, recent advances in computation-intensive methods open new opportunities for examining intersectional research questions at scale. These methods, exploiting massive, digitized datasets that include online text and images, medical records, geolocation trackers, administrative registries and social media, offer new insights into individual and group-level trends, including monitoring human mobility, human–environment interactions, intergroup relations, disease spread and various forms of inequality-generating processes[30–32]. In this Perspective, we offer a guide primarily for researchers, peer-reviewed journals and funding agencies in efforts to make quantitative intersectional approaches a standard part of research design in the natural sciences and technology, where relevant. Below, we explore how intersectional approaches function throughout the research process, discuss limitations and challenges of intersectional analysis, and offer a set of guidelines for intersectional research and reporting (Box 4 and Supplementary Information). The goal is to enhance rigour, accuracy and translatability in science and technology in efforts to promote social equity and environmental sustainability.

Intersectionality as an analytic approach

Intersectionality prompts researchers to consider the compounded disadvantages or advantages tied to socio-political dimensions, such as ethnicity, sex, gender, class, educational status or migration status, within specific social and environmental contexts. Specifically, we conceptualize intersectional factors at three interconnected levels: socio-political dimensions, contextual domains and environmental conditions (Box 2).

Not every study that examines the combined effects of social variables is intersectional, however. For instance, while variables capturing aspects of gender, race, and class are linked to instances of historical marginalization or differentiation across many regions globally, other variables, such as individual personality traits like openness or conscientiousness, may not be. To conduct an intersectional analysis, researchers must carefully explain how their chosen variables may reflect relationships of power, privilege and disadvantage[33]. Below we elaborate how such relationships may be conceptualized at different levels of analysis.

Socio-political dimensions

We use the term 'socio-political dimensions' to refer to the social categories and identity variables that are central to intersectional analysis. Social-political dimensions are not fixed; they are historically and culturally specific and change as societies change. In North America and Europe, much intersectional analysis has centred on sex, gender, race, ethnicity and class[2,4,34]. In other parts of the world, other social-political dimensions, such as caste-membership[35], urban–rural residence[36], religious affiliation or tribe membership[37] may require analysis. Unlike other terms (for example, social categories), 'dimensions' suggests that each category may include multiple sub-variables, sometimes operating at different levels of analysis. Sex, for example, is not simply binary, male and female, but at minimum includes also intersex, for instance, individuals with diverse sexual development (in humans)[38] and hermaphrodite (in non-human organisms)[39] individuals. Other biological aspects of sex include genetic, hormonal, genital and secondary sex characteristics[40]. Similarly, gender is a multi-dimensional concept that encompasses norms, identity, relations and institutional systems, each with their own sub-variables[41,42]. Socio-political dimensions, such as gender, can operate at the individual level (for example, gender identity) or at the contextual level (for example, gender norms and relations). The multiple complexities of sex and gender in research have recently been captured in the special sections devoted to these topics in *Cell*[43] and *Nature*[44], among others.

Social class, understood as "social groups arising from interdependent economic relationships among people"[45], is another important dimension that encompasses multiple sub-variables[46]. Unlike other socio-economic variables, such as occupation, educational status or income, which refer to individual attributes or properties, class emphasizes social relationships (for example, between an employee and employer), capturing individuals' positions in socially ranked hierarchies. Such relationships can be measured at the individual, household or community level and may vary over time and life-course[45].

Race is also complex: the word 'race' may be used as a proxy for many characteristics, including "racial identity, self-classification, observed race, reflected race, phenotype" skin tone or genetic ancestry[47,48]. Race, like gender, may operate at both the individual level (for example, racial identities and perceptions) and contextual level (for example, racial regimes)[49,50]. In some European countries, such as Sweden and Germany, the term is avoided in public documents and statistics with terms such as 'foreign origin' or 'migration background' being commonly used instead[51]. In other countries, race is reduced to discrete variables, such as the five racial categories and two ethnicities commonly used by the US census, or the typically four racial categories used in South Africa[52–54]. Recent machine learning research on racial health disparities highlights the limitations of such coarse codings, as variations within broad categories (for example, Chinese versus Indian under the broader category Asian) can exceed those across categories (for example, Asian versus Black)[55]. To overcome these limitations, AI models offer new approaches to measuring race as continuous variables or probabilities[56].

At the level of socio-political dimensions, experiences of power imbalances, privilege and disadvantage may be captured through survey-based self-reports of perceived stigma and internalized oppression[57] as well as exposure to discrimination[58] and microagressions[59]. Although such self-reported measures have their limitations[60], they enable researchers to shift their focus from the disparities between intersectional subgroups to the factors (for example, perceived discrimination) that mediate these disparities[61,62]. Additionally, field experiments can provide concrete evidence of direct discrimination facing various groups in real-world settings such as job markets[63], education[64] and housing markets[65].

Contextual domains

To fully capture relationships of power, privilege and disadvantage, researchers must also consider contextual domains (such as how socio-political dimensions relate to laws, policies, healthcare systems, educational institutions, criminal justice systems and religious bodies) and broader systemic factors (such as postcolonial legacies). These domains shape individual life choices and opportunities[66]. Take, for example, a recent study of disparities in heterosexual and lesbian women's birth outcomes in the USA[67]. Paying specific attention to variations in state-level protections of minority sexual groups related to employment, hate crimes, same-sex marriage and same-sex adoption, the study showed higher birth weights for infants born to lesbian women in states with good protection of minority sexual groups, averaging 3.71 kg compared with 3.01 kg in states lacking such policies. These policy differences did not correlate with the birth weights of infants born to heterosexual women[67].

Accounting for the legacies of discriminatory laws and regulations may also offer important intersectional insights. US researchers have studied the long-term consequences of inequitable housing policies, showing that many decades after these policies were abolished, adverse health outcomes persist at the intersection of race, ethnicity and geographic location, disproportionately affecting minority populations in historically redlined neighbourhoods. This included higher rates of preterm births[68], elevated cancer stages at diagnosis[69] and increased environmental risks such as urban heat islands[70]. Another US study developed a measure of race regimes, showing how historical state-level differences in enslavement, sharecropping, disfranchisement and segregation help explain contemporary state-level variations in Black–white poverty gaps[50]. Together, these examples demonstrate that, without attention to relevant contextual factors, intersectional analyses risk overlooking the root causes of subgroup disparities, resulting in a weaker basis for designing targeted interventions. Contextual measures of power, privilege and disadvantage may also be captured through population-level estimates of attitudes on issues such as gender and sexism[71–73], racism[74,75], genderism and transphobia[76], derived from representative surveys or area-specific internet searches. For instance, one recent study used an internet-based measure of area racism (the proportion of Google searches from a region containing racial slurs) to test associations with Black mortality rates, illustrating a link between location-related racial attitudes and health outcomes[77]. In another study, researchers used survey data on essentialist gender norms from 64 countries to document how stronger gender stereotypes about mathematics at the country-level predict women's lower participation in science, technology, engineering and mathematics (STEM) fields[78].

Environmental conditions

Considering environmental conditions such as air, soil and water quality may also offer novel perspectives in intersectional analysis. The field of environmental justice has pioneered research on this question[79], for example, by documenting how urban segregation along racial and socio-economic lines, combined with the uneven placement of hazardous facilities, disproportionately exposes marginalized communities to environmental toxins and pollution[80,81]. Plastics and plastic-associated chemicals are also responsible for significant harms to human and planetary health that are not evenly distributed by geographic location and occupation[82,83]. Coal, oil and gas workers who are extracting fossil carbons and residents of nearby communities face higher mortality rates from silicosis, cardiovascular disease, chronic obstructive pulmonary disease, lung and bladder cancer, leukaemia and lymphoma[84–87]. Here geographic location intersects further with age. Infants and children in communities near sites of plastic production are particularly at high risk for plastic-related health effects during early physical and cognitive development[88]. A disproportionate burden of illness and mortality due to climate change is also borne by minority racial and ethnic groups, migrants and Indigenous communities, particularly in, but not restricted to low-income countries[89]. Other characteristics such as age, sex, disability, gender, sexuality and class can exacerbate or mitigate experiences of discrimination, compounding the impact of climate change on health[90]. Heat exposure and climate migration differ along socio-political dimensions, with evidence from South Asia suggesting that men are more likely than women to migrate and that those who are married, have higher levels of education and are between 20 and 40 years of age are the most mobile[91]. Higher heat exposures are often associated with areas with high proportions of minority racial and ethnic groups, low socio-economic status, outdoor workers and homes in need of retrofitting to combat climate change[92].

Capturing relationships of power, privilege and disadvantage linked to environmental conditions requires attention to geographic and community-level variations. Fundamentally, this involves identifying who is most likely to be at risk from environmental hazards and climate-related disasters, and who is most likely to be protected and resilient. In environmental hazard studies, demographic data from sources such as census tracts are sometimes used to highlight intersectional disparities in air pollution[93] or heat exposure[94]. Similarly, researchers have used spatial analyses of aggregated demographic data to explore compounded social vulnerabilities in the spatial distribution of hazards related to disasters, such as Hurricane Harvey in the USA[95], flooding in Chennai, India[96], and droughts in Northeast Brazil[97]. Understanding the power relationships underlying such disparities may also require attention to national and local governmental priorities, including variations in disaster aid allocation and in programmes aimed at recovery and future disaster prevention[98,99]. Moreover, it may involve shifting focus from the most vulnerable populations to those who contribute the most to environmental threats. For instance, an influential ethnographic study demonstrates how conservation efforts, which are intended to preserve natural spaces, can reinforce environmental inequalities, enabling wealthier communities to enjoy the privileges of conservation while excluding marginalized ethnic and racial communities[100].

Stepping through the research process

A first step in conducting intersectional analysis is to build an inclusive research team whose knowledge or practical experience is relevant to the proposed project. Ensuring diversity within the team[101–103] and involving a wide range of research subjects and end users throughout the research cycle—from problem definition to design and implementation—can enrich outcomes by encouraging attention to the varying needs, interests and lived realities of specific subgroups[104]. In areas such as health, climate change, technology and sustainability, collaborating and co-designing research with affected communities can also produce more equitable solutions[105–108]. However, successfully engaging diverse marginalized populations will often require recruitment strategies that consider possible barriers to participation[109] and power imbalances between researchers and participants[110].

An important second step is to set research priorities. Any one research project cannot capture all socio-political dimensions. Researchers will typically start broad and narrow the project to prioritize key intersections as these emerge through the investigative process itself[111]. Systematic literature searches can be helpful to foreground specific (contextual, place-based, time-based or region-based) instances of historical discrimination for in-depth intersectional analysis. In studies where data annotations are abundant, such as some AI applications or large health surveys, machine learning algorithms in the form of, for example, decision trees may be used to uncover the socio-political dimensions of interest[112]. However, such approaches often require large and diverse samples. Recently, AI researchers have focused on developing more sample-efficient methods for intersectional data exploration based on structured regression and Bayesian techniques[113,114]. These methods enable reliable estimates even for small subgroups, when sample sizes are constrained.

Data collection

Strong intersectional research hinges on quality data, and requires careful consideration of the categories that structure the data and the systems of power that might have shaped them[115]. Even in the social and health sciences, where large-scale population surveys are common, detailed information on socio-political dimensions (such as sub-variables for sex, gender or class) and measures of power, privilege and disadvantage (such as perceived discrimination and stigma) are often missing. Many questionnaires, administrative data sources and electronic health records, for instance, do not capture the complexities of biological sex and gender identities, limiting their relevance for intersectional research[116,117]. Treating sex assigned at birth as a proxy for gender identity risks diminishing the relevance of the data, particularly in analyses that seek to capture the experiences of minoritized identities. To remedy this shortcoming, researchers increasingly deploy a two-step method in survey questionnaires that measures sex assigned at birth and self-reported gender identity separately[118]. Achieving adequate representation of marginalized groups poses additional challenges when researchers collect survey data. Researchers may need to strategically over-sample specific marginalized subgroups to ensure sufficient statistical power for intersectional analysis[119].

Despite drawbacks, intersectional analysis sometimes requires the use of proxy variables, particularly when data access is limited or when collecting specific demographic information (for example, sexual orientation) poses a risk to participants[120]. For instance, when health records lack demographic markers, algorithms may be used to impute such information from auxiliary data. Research shows that AI can predict a patient's sex[121] (in a binary fashion only) from X-ray images in ways that humans cannot. Although imputed data can be beneficial, such as for forensic evaluations during emergencies, it may also introduce bias into AI models, potentially affecting downstream analyses and ultimately, health outcomes[122,123]. Lack of fine-grained data may also require a shift in focus from individual-level analysis to a broader community-level perspective through geospatial methods. A recent study used geospatial data to uncover differences in parental care seeking for medical treatment for young boys and girls in Ethiopia. Combining data on care seeking and community-level characteristics, the study highlighted that religion, but not socio-economic status, predicted gender differences in parental care seeking, with preferential care seeking for boys being especially pronounced in Muslim-majority communities[124]. Here, aggregated community-level variables helped to reveal dynamics that could inform more culturally sensitive interventions to mitigate such disparities.

Robustly diverse data are also important for AI models. When models designed for general applications are exposed to a wide range of images, linguistic styles, topics and cultural contexts, they perform more accurately across various scenarios[125,126]. For instance, recent experiments with large language models in clinical applications reveal that GPT-4 amplifies stereotypes of diseases that are present in its training data, such as cases of sarcoidosis in Black women patients, over and above true prevalence estimates, putting other demographic groups at risk of underdiagnosis[127]. The capability of generative AI to create new data (for example, synthetic images or simulated clinical data) that exacerbate biases in existing data also highlights the critical need for thorough intersectional analysis of these models. Without appropriate guardrails, biased synthetic data can propagate through media, educational materials or even training data for future AI[128]. Recent guardrails by companies have tried to bluntly over-sample historically underrepresented groups in their generations. This too has led to controversies (for example, Gemini generating images of Black women popes), further highlighting the challenge and need for thoughtful intersectional analysis in AI[129].

Methods

Conventional statistical models are often, by default, non-intersectional. A typical multiple regression might assess variables such as gender, race and ethnicity separately, as if they operate independently. This additive method[130] provides estimates for each variable but ignores their interdependent effects. Contrast this with an intersectional approach, which seeks to understand the multiplicative effects of these variables. This issue arose in a paper in the *New England Journal of Medicine* that examined how sex, race and age affected physicians' referral rates for the management of chest pain[131]. Although the study included an interaction term among its analyses, subsequent narratives both from the authors and in media reports, focused on the main effects. This led to the broad statement that both race and sex independently influenced physician recommendations. Yet, the interaction analysis showed something else. Black women, but not white women or Black men, had notably lower referral rates than white men—a detail that was lost in the main effects interpretation[119,132]. Failing to properly interpret the data meant that patients might have received inadequate treatment.

Strong quantitative intersectional analyses require methods that can produce reliable estimates at the intersection of multiple variables that capture socio-political dimensions (for example, gender ∩ sexual orientation ∩ immigration status) that possibly vary across contexts (for example, countries, regions, schools, hospitals or neighbourhoods) and environmental conditions (such as air, soil and water

Box 3

Five key challenges and initial strategies to address them

(1) **Identifying relevant variables**
- Challenge: Identifying relevant socio-political dimensions, contextual domains and environmental conditions may be difficult.
- Strategy: Conduct thorough literature searches on the role of intersectional factors in your domain. When working with large, detailed datasets, machine learning techniques such as decision trees may help identify key factors in your data.

(2) **Defining and measuring intersectional factors**
- Challenge: Precisely defining and measuring complex variables, such as race and gender, can be challenging; these variables may interact in unpredictable ways, especially when additional intersectional factors are taken into account.
- Strategy: Draw on established guidelines, checklists and recommendations for operational definitions of each key factor. Consider adding a humanist or social scientist to your team.

(3) **Lack of relevant attributes**
- Challenge: Many existing datasets do not contain detailed measures of socio-political dimensions, contextual domains or environmental conditions, limiting the scope of intersectional analysis. This deficiency can stem from historical biases in data collection, privacy concerns or simply oversights in study design.
- Strategy: Even with imperfect data, intersectional approaches may nonetheless generate new insights and research questions to guide future studies towards more detailed data collection. Consider proxies that can cover aspects of the socio-political dimensions, contextual domains or environmental conditions relevant to your research design.

(4) **Limited resources and sample size constraints**
- Challenge: Many researchers work with limited sample sizes owing to constraints in time, funding or participant access. These limitations reduce statistical power, making it difficult to analyse intersectional subgroups effectively.
- Strategy: Focus on the subgroups for which you have sufficient sample sizes and consider oversampling underrepresented groups of interest. Pool data from multiple studies where possible to increase statistical power. Sample-efficient methods such as structured regression or Bayesian techniques can enable reliable estimates for subgroups, even with smaller samples.

(5) **Lack of contextual knowledge**
- Challenge: Unfamiliarity with socio-political contexts can hinder the integration of intersectional analysis in technical fields.
- Strategy: Engage with social science literature, foster transdisciplinary collaborations with experts in these areas and consider using strategies that support greater community engagement across the research cycle.

quality). However, regressions with interaction terms are not always optimal. They often require large sample sizes and can be difficult to interpret once interactions exceed two variables, especially when continuous measures (for example, income) or factor variables with numerous subcategories are involved. Advanced techniques, such as the group-lasso interaction network, impose fewer parametric assumptions than moderated regression models, reducing the risk of over-specification and providing more stable subgroup estimates when sample sizes are small[133]. Some researchers also advocate for the advantages of multi-level models that partition differences in outcomes into between-strata (capturing variance between genders, races, age groups and other groups) and within-strata (capturing variance within these groups) to enable more efficient estimation and interpretation of complex interactions[134–136]. Decomposition methods have been used to parse out the mediating effect of perceived discrimination on social disparities in psychological distress across intersections of gender, race and sexual identities[62]. In epidemiology, researchers have used the population attributable fraction—a method for quantifying prevalence and excess risk—to estimate differences in the contribution of various factors (for example, hypertension, obesity and diabetes) to health failure across race–sex groups[137]. Cumulative risk models, in turn, quantify the combined effect of proven factors associated with an outcome. These models may be used to approximate the cumulative risk (for example, the combined effect of poverty and access to decent housing) that climate-related events pose to vulnerable groups[138,139] or how various types of minority stress (for example, experiences of identity-based discrimination, harm and parental rejection) predict suicide among LGBTQ and minority ethnic groups[140].

Additional statistical approaches that are relevant for intersectional analysis include directed acyclic graphs and structural equation modelling, which enable researchers to determine the direct and indirect pathways by which environmental, contextual and individual-level factors relate to intersectional disparities[141,142], geographically weighted regression, which enables estimations of how relationships between intersectional variables and outcomes vary across locations[143], latent variable and clustering methods, which enable researchers to classify subjects into subgroups based on experiences of stigma or discrimination[144] and subset scanning, which enables researchers to identify heterogenous effects[145] (for example, by focusing on the intersectional subgroups that diverge the most from a predicted outcome). Since the compounded privileges or disadvantages that individuals face can shift over time and across settings, quantitative intersectional studies may often benefit from longitudinal, panel-based designs[146] and contextual comparative techniques, such as hierarchical[147] and cross-classified models[148].

Although advancements in quantitative methods open promising new opportunities for intersectional research, these approaches have their limitations and may often be fruitfully complemented by qualitative approaches (for example, focus groups, interviews and ethnographic observations) to gain deeper insights into the micro-social processes, mechanisms and contextual factors that drive intersectional inequalities. Oral histories[149] and traditional or communal knowledge[150] can also enhance the quality of quantitative intersectional research data, providing broader insights often missing from purely digital or written records.

In AI, one key methodological challenge is to get the model right. Whereas AI models may show high accuracy at aggregate levels, they sometimes fail for specific subgroups[151]. It is crucial to identify such errors for a deeper understanding of the model's limitations[152,153]. Effective interventions for model improvement may be implemented at various stages of the machine learning process: pre-processing to detect and address biases in training data, in-processing to optimize models for fairness, and post-processing to modify model outputs for fairer predictions[154]. Multiple fairness metrics are being tested to mitigate intersectional bias in algorithmic decisions across domains, such as news article recommendations, facial recognition, criminal sentencing, healthcare diagnostics and environmental justice. One such metric, multicalibration, helps to ensure reliable predictions

Box 4

Guidelines for reporting intersectional analysis in science and technology

Title and abstract
In studies where intersectional analysis is central, signal that in the title. Where intersectional analysis is included in results, indicate this in the abstract and specify the populations and socio-political dimensions covered.
Introduction
Specify the background, rationale, objectives and hypotheses for intersectional analysis. Detail the socio-political dimensions covered and consider how they may reflect relationships of power, privilege and disadvantage. Highlight relevant findings from similar or past studies to contextualize the current study.
Methods
Offer precise definitions for each socio-political dimension. Describe how each is measured. Describe the methods used to examine their intersectional effects, and explain how you account for relevant contextual domains and environmental conditions. Intersectional approaches are usually multiplicative, not additive, implying a focus on compounded effects. Specify the required sample sizes for each subgroup to ensure sufficient statistical power.
Results
Detail the sample's composition across the intersectional dimensions. Disclose all outcomes, including null results. Report within-group variability and between-group overlap to avoid overemphasizing differences. Make raw data accessible for pooling while ensuring anonymity.
Discussion
Summarize key intersectional results and discuss limitations, whether due to study scale, data availability or other factors. Discuss whether the results generalize to other populations. Reflect on how the results connect to questions of power, privilege or specific contextual domains and environmental conditions.

across identifiable subgroups within a given computational framework[155]. We note that such metrics rely on representational models and data as well as competing theories of what constitutes fairness, which have not been settled[156]. These competing theories encompass notions of individual fairness, which focus on ensuring equal treatment for individuals with similar qualifications, and notions of group and subgroup fairness, which aim to achieve equal outcomes across different demographic subgroups[157].

Limitations and challenges

Although intersectional approaches can lead to more precise, efficient and representative scientific outcomes, they might not be applicable in research areas without direct or indirect human implications, such as pure mathematics, theoretical physics or certain subfields of chemistry (for example, polymer synthesis and chemical reaction dynamics). Even in areas with apparent human impacts, these approaches can be challenging owing to their complexity, costs and limited expertise among researchers (Box 3). Developed in the humanities, social sciences and health sciences, these approaches have, for the most part, not made their way to other fields, highlighting a need for integration into the core curricula of natural science and technology[158,159]. Funding agencies may also lack the proper incentive structures to encourage this type of research[160], while in some regions, limited access to resources and relevant infrastructure could constrain the capacity to use the more data-intensive and computationally heavy intersectional approaches[161]. However, although intersectional analysis often requires greater initial investment from funding agencies, institutions, and research leaders, it may ultimately lead to more precise, efficient and representative scientific outcomes[162,163]. In the long term, this may reduce costs by supporting more effective and inclusive policies or technological solutions. Nonetheless, systematic assessments of the specific costs and benefits of intersectional analysis for scientific advancement and broader societal benefits remain a promising area for future research.

Guidelines for quantitative intersectional analysis

Intersectional analysis is evolving quickly and, as this Perspective has illustrated, requires sophisticated approaches to yield rigorous results in quantitative research. The pillars of science infrastructure—including funding agencies and peer-reviewed journals—must implement coordinated policies to support this kind of research[41]. At the beginning of the research process, funding agencies can ask applicants to explain how intersectional approaches might be relevant to their proposed research, or to explain why they are not[164]. At the end of the research process, peer-reviewed journals can encourage intersectional analysis where relevant, and consider it as a factor in publication decisions[165]. To ensure excellence in research, peer-reviewed journals have already adopted guidelines for reporting sex and gender, most prominently the Sex and Gender Equity in Research (SAGER) guidelines[166,167]. Similarly, many journals, including *JAMA*, *Nature* and *The Lancet*, have published guidance for reporting race, ethnicity and other social variables[48,168,169]. However, clear guidance on quantitative intersectional analysis is still lacking, although there is wide agreement that such guidance is needed. We aim to fill this gap by offering guidelines for research and reporting intersectional analysis in science and technology (Box 4 and Supplementary Information).

Conclusion

Much work remains to be done to systematically integrate intersectional analysis into relevant domains of the natural sciences and technology. By developing better guidance and support systems for quantitative intersectional approaches, journals, universities and funding agencies can raise the bar on rigour, accuracy and translatability in science.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-025-08774-w.

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