Gender and Sex in the Computer Graphics research literature

Ana Dodik* — Meta Platforms
Silvia Sellán* — University of Toronto
Theodore Kim — Yale University
Amanda Phillips — Georgetown University

ABSTRACT

We survey the treatment of sex and gender in the Computer Graphics research literature from an algorithmic fairness perspective. We conclude established practices on the use of gender and sex in our research community are scientifically incorrect and constitute a form of algorithmic bias with potential harmful effects. We propose ways of addressing these trends as technical limitations.

1 INTRODUCTION

References to sex and gender can be found all throughout the Computer Graphics research literature: a dataset is said to contain images of men and women, user study participants are reported to have a certain male/female ratio, a body modeling algorithm trains two different gendered models, a voice modification method is said to work on male and female voices, etc.

The scientific consensus around the concepts of sex and gender has greatly evolved in the past decades (see, e.g., [Nature Editorial Board 2018]). As surveyed by Fausto-Sterling [2012], *sex* is not one but a combination of many biological classifications (*chromosomal sex, hormonal sex, reproductive sex, ...*) which cannot be unambiguously assigned in a binary way to as much as one in 50 people [Blackless et al. 2000]. *Gender*, on the other hand, is used to refer to an individual's self-identity [Money and Ehrhardt 1972], their performance of certain acts as shaped by social expectations [Butler 2003] and arbitrary organizational structures that segregate people in different public bathrooms and even decide who can access education [Lorber 1994]. By all these contemporary definitions, gender is non-binary, fluid and culturally-specific. Furthermore, assuming outdated binary definitions of sex and gender is not just scientifically incorrect, but is also harmful (see [UNHCHR 2015]) to those who conform the least to this artificial binary (e.g, *intersex*, *transgender*, *non-binary* people), to whom we will onwards refer to as *gender non-conforming* individuals.

Disappointingly, we observe that the treatment of sex and gender in SIGGRAPH Technical Papers still answers to a traditional binary understanding of it that excludes intersex and many transgender and gender non-conforming people. In what follows, we will use an algorithmic fairness perspective to argue that this introduces forms of algorithmic bias that harm our scientific integrity. We will examine the harmful real-world consequences of the algorithmic bias introduced by our modeling choices with respect to gender on how gender non-conforming people interact with our technology in their daily lives. We will advocate for reexamining our treatment of gender and show that this will not only correct problematic practices established in our community, but also open the door to whole new avenues of research.

2 SURVEY

Inspired by the work of Keyes [2018], we conducted a survey of all technical papers presented at SIGGRAPH North America and SIGGRAPH Asia since 2015 (see *Supplemental Material*). We observed references to sex and gender routinely throughout, varying in nature from demographic information reported about user study participants to gender-specific algorithms. Whenever gender or sex is used explicitly as a variable, it is always as a binary one. Sex and gender are never given a precise definition in all the reviewed literature, and appear to be used implicitly as a proxy for anything from body proportions to facial expression to patterns in speech.

An analysis of the above from an algorithmic fairness perspective (Section 3) reveals a worrying status quo in the use of gender and sex as variables in Computer Graphics. As we mention examples of works that perpetuate these trends, we stress that we do not associate any malicious intent to any. Rather, we wish to show how seemingly neutral, well-established practices in our community can lead to us unwittingly perpetuating forms of algorithmic bias.

3 ALGORITHMIC FAIRNESS ANALYSIS

Our survey shows that the current use of gender and sex in the Computer Graphics literature is at best ill-defined, and at worst incorrect. In this section, we apply the framework of Suresh and Guttag [2021], which categorizes types of bias according to the stages of a system's lifecycle (see also [Friedman and Nissenbaum 1996; Mehrabi et al. 2021; Olteanu et al. 2019]) We give examples of how different types of bias occur in our surveyed work and show that these are *technical* limitations that impede our community's goal of producing precise, high-quality and reproducible research.

Representation bias. A part of a population may be poorly represented by a dataset, for example, because the sampling procedure is biased not to include people of non-binary genders (*sample selection bias*) or because no care is taken to ensure algorithms perform equally well in groups of *underrepresented* sex or gender. Despite the prevalence of these individuals in the general population, we could not identified a single paper (O3) that explicitly mentioned them as part of datasets (O5) or user study participants (O6). The sampling procedure may have been accidentally designed to exclude these individuals, or it might be due to measurement bias. We did not identify any work that explicitly analyzed any type of representation bias experienced by gender non-conforming individuals (O1).

Historical bias. Data, despite being abundant and perfectly sampled, may encode existing prejudice. For example, a *gender classifier* (O7) trained on portrait image data collected in a society where social norms dictate gender expression might learn that "wearing a dress" means woman, and "short hair" means man.

Measurement bias. Bias may be introduced through the selection and measurement of features and target variables. We observed that many works use sex or gender as imprecise *proxies* (O4) for attributes like *commonly co-occuring bodily characteristics* or *speech characteristics*, where it is possible that the authors would be better served using other less abstract features (e.g., hair length, or voice

*Joint First Authors

pitch). We even observed works that combine several of these proxies into one; for example, conversational agents that use gender to refer to both voice pitch *and* culturally acquired speech inflections.

Furthermore, when gender or sex was chosen as a feature or target variable, it was always (O1) through an *inaccurate method of measurement* (treating gender as a binary variable, non-binary individuals cannot be captured by design even if they are in the dataset) and often (O7) through an *incorrect method of measurement* (using image-based gender classifiers as opposed to self-identification, gender non-conforming individuals may be misidentified).

Omitted variable bias. The success of using a certain feature may be overemphasized if it correlates with another important feature that has been omitted from the model (see e.g., [Clarke 2005]). For example, *gender* or *sex* are likely not as discriminative as variables when the result is also conditioned on *hair length*, *hip width* or *mean voice frequency*. In our survey, where gender or sex's use was justified because of an assumed improvement in model accuracy (O4), we found no effort to indentify if the success was due to omitted variables.

Evaluation bias. These are biases introduce during the evaluation of an algorithm. For example, we observed works in body modeling that provide binary segregated parametric models (O3). We observed these being used to evaluate *other* works with orthogonal contributions, like virtual try-on or motion capture. If our research community settles on benchmarks with biased data, the development of models that conform to those biases is encouraged.

Deployment bias. The effects of algorithmic bias do not stop at the publication stage; rather, harm is introduced as a consequence of a model being deployed or published in the real world. For example, the publication exclusively of papers with a binary understanding of sex and gender incentivizes researchers (and reviewers) to conform to that definition (O1). This can also lead to *feedback loops*: if, as we have observed, gender non-conforming people are not included in a virtual clothing try-on system, they are less likely to use them, causing the data about the performance of such a system to be skewed to include fewer gender non-conforming people. Finally, a biased system can cause further bias by nudging users to artificially change their behaviour: for example, a trans person might feel the need to change the pitch of their voice in order to not get misgendered by an algorithm, thus also skewing the collected data.

3.1 Real world harm

The discussed technical limitations of the reviewed algorithms are not only academic in nature, but can and do lead to real world harm. As Computer Graphics is being increasingly applied to other fields, such as for processing geometric data in medicine, or for synthetic dataset generation in computer vision with numerous downstream applications [Behzadi 2021; Brewer 2020; Chen et al. 2021], it is paramount to understand that our algorithms can and will be used in novel ways potentially causing harm in ways we did not intend.

The algorithmic fairness literature disambiguates between representational and allocative harms [Barocas et al. 2019].

Representational harms. These encompas the perpetuation of harmful stereotypes or cultural norms that subject individuals to denigration. For example, it is well documented that airport body scanners routinely subject gender non-conforming passangers to public humilliation [Beauchamp 2019].

Allocative harms. These are caused when certain groups are denied access to an opportunity or a resource because of algorithmic bias. For example, a virtual try-on experience based on the algorithms in our survey might accidentally exclude precisely the people with non-normative bodies who are most in danger in traditional physical changing rooms [Silver 2017].

Finally, ignoring the existence of gender non-conforming individuals in our research (O3) creates an alienating and exclusionary environment for gender non-conforming members of our very own research community, going directly against SIGGRAPH's goal to be *a model of inclusion, equity, access and diversity for all.*

4 WHERE DO WE GO FROM HERE?

Our analysis reveals that the common use of sex and gender in the Computer Graphics literature can pepper our research with algorithmic bias. Our disambiguated study shows bias is introduced all through the modeling process; thus, we argue algorithmic fairness cannot be an afterthought but rather present at all stages of our research. While we have focused on sex and gender, we hope our work contributes to the broader conversation about algorithmic fairness in our field, which includes racial biases [Kim et al. 2021].

While different real-world constraints might not make it realistic for a research group to successfully mitigate certain sources of bias, the potentially introduced biases should at the very least be acknowledged. For example, none of the reviewed papers included any of the various algorithmic fairness metrics (for a summary, see [Mehrabi et al. 2021; Pessach and Shmueli 2020]) in their evaluation, nor did they even include a discussion of the potential harm their methods could be causing by their treatment of sex and gender.

Further, we argue that the issues raised by our survey are not only potentially harmful to under-represented populations, but also often *scientific* limitations which are not well researched. If a method cannot model a class of humans by design, or if a production system fails for a subsection of the population, these are fundamental *technical* limitations that should be discussed as such.

We believe gender and sex can have a place in our research. For example, it is probably advisable to report them among demographic statistics of datasets or user study participants (as long as they are self-reported and treated as non binary in agreement with the scientific consensus) to safeguard against the "male default" plagueing our science. In most other cases we observed, however, we argue gender or sex could and should have been replaced by other, more accurate variables.

It bears mentioning that our observed entrenchment in sex and gender as relevant variables is a rare example of Computer Graphics research lagging behind the needs of our partner industries. The latest photorealistic character modeller by Unreal Engine [2021] and the Cloud Vision API by Google [2020] have removed all references to sex and gender. Video games as diverse as *Animal Crossing* and *Forza Horizon* completely decouple attributes like body proportions, voice pitch, hairstyle and prononouns from one another.

We acknowledge that our proposed break with tradition may bring with it effort and difficult conversations, but these are challenges worth facing in the interest of scientific advancement as well as producing a fairer, more inclusive future.

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