
Request for Information (RFI) on Public and Private Sector Uses of Biometric Technologies: Responses

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“Garbage in, garbage out” is a computer science phrase referring to the problem of poor-quality inputs leading to poor-quality outputs. Charles Babbage first expressed the idea behind the phrase in his autobiography about his experiences as a mathematician in Victorian England. Although not directly connected, his idea is key to understanding contemporary debates regarding facial recognition technology (FRT), including the data auditing of FRT algorithms. This comment explores the term GIGO; considers its application to FRT; and proposes best practices to address the issue, including establishing minimum photo quality and editing standards, annual algorithmic audits, and allowing governments and companies to purchase only the most sophisticated software trained on representative data. The comment's critical approach foregrounds analysis of the connection between evidence and identification tools built on computer algorithms. Independent research was conducted as part of an undergraduate course in communication at the University of Pittsburgh. Younger generations are surveillance natives; therefore, when we believe a technology crosses the line, the potential negative impacts of that technology must be severe.
History of GIGO

According to the *Oxford English Dictionary*, the first known printed usage of the phrase “garbage in, garbage out” dates to 1957 (“garbage”). At the time, high-speed computers had to be manually programmed, and data typically was inputted using punch cards or tape. In the article “Applying New Electronic Computers to Traffic and Highway Problems” for *Traffic Quarterly*, Dr. Ernst E. Blanche uses the acronym “GIGO” for the phrase “garbage in, garbage out,” which “emphasizes that the results are no better than the data given to the computer” (411). The concept, however, is much older and dates to Victorian England.

Compared to mainland Europe, mathematical innovation in Great Britain had stagnated from 1750 to 1830 due to the island’s isolated geographical location, war with France, and distrust of new ideas in the field (Flood et al. 2). Queen Victoria assumed power in 1837 and presided over a social, economic, scientific, and technological Golden Era for Britain. In his autobiography *Life from the Passages of a Philosopher*, Charles Babbage retells his development of the Difference Engine Number One, the first prototype for an automated calculator. Seeking to reduce the mental labor and frequency of error in calculations, the object of the Difference Engine was to “calculate and print a series of results formed according to given laws,” called “tables” (Babbage 38). In 1823, seeing a potential use for nautical calculations, the government agreed to finance the development of a large-scale Difference Engine and granted Babbage 1,500 pounds from the Civil Contingencies fund (Babbage 52). Between 1823 and 1842, the government spent over 17,000 pounds on Babbage (Babbage 68). During his progress checks with the government, Babbage had been asked by two members of the House of Lords and the House of Commons respectively, “‘Pray, Mr. Babbage, if you put into the machine wrong figures, will the right answers come out’” (qtd. in Babbage 50)? Babbage dismissed the
question as a misunderstanding of the machine’s design. However, given the state of calculators at the time, the representatives’ confusion was warranted.

At the time, slide rulers and printed mathematical tables were primarily used for calculations (Flood et al. 243-244). These devices were “mechanical,” meaning that “useful operation relied on the continuous informed intervention of the operator” (Flood et al. 245); essentially, if the operator made a mistake, the output would be inaccurate. Babbage’s Difference Engine, which operated by steam, was the first automated calculator, meaning “it embodied mathematical or computational rule in mechanism” (Flood et al. 250). The calculator was programmed ahead of time, and the operator, having nothing to do with the input, only needed to pull a lever.

Perhaps the question that the members of Parliament posed to Babbage seemed inane and ignorant—they did not understand the concept of automated calculation. However, their concerns have returned full force today with the increasing use of facial recognition technology. FRT does, in fact, require the informed intervention of the operator, specifically relating to probe photo editing. Low quality or overly edited probe photos will lead to garbage outputs. In addition, improperly trained algorithms will inevitably produce garbage, no matter the quality of the input.

**FRT and Data Audits**

There are two broad categories of FRT: one-to-one identification and one-to-many identification. One-to-one identification is when a person’s identity is verified from a photo of them, such as when a smartphone matches a photograph on file with a user’s face to unlock the phone (Castelvecchi). One-to-many identification is when a person’s photograph is matched to
multiple photos contained in a database (Castelvecchi). There is also a third related category of FRT—demographic and behavioral classification. Clare Garvie specifically examines the second category. According to her, police departments often feed “celebrity lookalike” images, police sketches, poor quality images, and substantially edited photos into facial recognition algorithms ("Garbage In"). These practices reduce the accuracy of the algorithm—feeding a computer bad information ("garbage") leads to inaccurate results (more “garbage”). According to a recent National Institute of Standards and Technology report, there have been huge gains in accuracy since 2013, although “only the most accurate [algorithms] excel on poor quality images and those collected long after the initial enrollment sample” (Grother et al. 6). However, what happens when the input is good, but the data on which the algorithm has been trained is garbage?

Facial recognition relies on datasets that train algorithms to produce certain outputs when certain data is inputted (Lee et al.). Essentially, algorithms are trained through supervised learning, a process in which mated and non-mated pairs of photos are shown to a computer and the computer must find the shortest route to matching the mated photos (“Personal communication”). For example, researchers in one study trained a computer algorithm to distinguish between photos of dogs and wolves. The algorithm succeeded, but researchers soon learned that the algorithm was sorting the wolf photos together not by physical features but by detecting snow in the images; as a result, the study was a failure (“Personal communication”). How the computer comes to its conclusions is a “black box”; even developers are oftentimes unsure of the computer’s methods (“Personal communication”). This becomes especially problematic if the pairs of photos come from unrepresentative or incomplete datasets; bias can easily be codified into an algorithm (Lee et al.).
In tax audits, algorithms review whether filers pay their fair share. Algorithm audits assess how well machines are doing their jobs. These latter audits can be conducted in two ways: first, by examining the algorithm’s code and data and, second, by interviewing company stakeholders about the perceived impact of the algorithm (Ng). In the Gender Shades study, a group of MIT researchers, using the first method, found that one technology company’s gender classification system had a 97% accuracy rate (Hardesty). However, this number was based on a dataset that was 77% male and over 83% white, and the algorithm’s accuracy rate dropped substantially for women with darker skin (Hardesty). Although the Gender Shades study focused on gender classification algorithms, many facial recognition algorithms are trained in much the same way. Some scholars promote regular audits, arguing that they produce insightful information and encourage companies to reexamine bias in their algorithms. However, algorithmic audits also create a set of ethical concerns.

A recent controversy is HireVue’s use of a facial recognition algorithm in assessing video interviews of candidates for hire. HireVue turned to a third-party auditing company, O’Neil Risk Consulting & Algorithmic Auditing (ORCAA), which consulted Hirevue stakeholders and found no evidence of bias in company procedures (Ng). However, HireVue has come under fire for using this audit as a public relations stunt. ORCAA’s audit targeted a specific section of the company’s procedures and did not evaluate the algorithm or data, yet HireVue proclaimed the audit’s success (Ng). Are data audits truly useful, or are they simply ways for companies to gain positive publicity? In addition, Raji and colleagues warn against overreliance on algorithmic audits, finding several ethical concerns. One such concern is that expanding the dataset for facial recognition technology requires the increased surveillance of minority communities, creating issues of privacy and consent (Raji et al. 4-5).
Recommendations and Conclusion

Ideally, due to the “garbage in, garbage out” problem in FRT, I would recommend against the use of facial recognition technology in all fields. However, I realize that this is unrealistic, as use of FRT is likely to increase in the future. Instead, I propose three best practices. First, as Garvie recommends, governments and companies using facial recognition must establish minimum photo standards for probe photos (“Garbage In”). Organizations such as the International Organization for Standardization and other scholars in the academic community are developing specific image quality thresholds for an algorithm to accurately make a match (“Personal communication”). On a related note, certain photo edits should be prohibited. As Garvie argues, adjusting an image for lighting and coloring is minimally problematic, but substantial edits such as copying and pasting other people’s facial features onto a probe photo should be unacceptable (“Garbage In”).

Second, companies should have annual data audits of the technical type. Audits should thoroughly test the algorithm’s data and code and seek to highlight biases present in the underlying datasets. Finally, I recommend that governments and companies be allowed to purchase only the most accurate algorithms available that have been trained on representative data. Due to the disparity in accuracy rates between various algorithms, governments and companies should only purchase those that can match faces with a high degree of accuracy across all demographics. Raji and colleagues’ concerns about infringing on the privacy rights of minorities are real. However, instead of fighting the losing battle against FRT, we should work to make algorithms equally accurate for non-white males. Further, datasets that target minorities should be sequestered and constrained to auditing purposes only; in addition, such datasets should only contain images of people who can explicitly opt in and opt out of inclusion. By
taking these steps, we can minimize the likelihood of the “garbage in, garbage out” problem in FRT.

In conclusion, the phrase “garbage in, garbage out” originated in a 1957 *Traffic Quarterly* article, but the idea behind it dates to Victorian mathematician Charles Babbage’s Difference Engine. “Garbage in, garbage out” may not have been a problem for Babbage, but it is an increasingly large one today with the frequent use of biased facial recognition technology. Only with proper safeguards can the issue be properly managed.
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