TOWARDS ETHICAL BIOMEDICAL INFORMATICS: LEARNING FROM OLELO NOEAU, HAWAIIAN PROVERBS

Peter Y. Washington

Department of Information & Computer Sciences, University of Hawaii at Manoa
Honolulu, HI 96822, USA
Email: pyw@hawii.edu

Noelani Puniwai

Kamakakuokalani, University of Hawaii at Manoa
Honolulu, HI 96822, USA
Email: npuniwai@hawaii.edu

Martina Kamaka

Department of Native Hawaiian Health, University of Hawaii at Manoa
Honolulu, HI 96822, USA
Email: martinak@hawaii.edu

Gamze Gürsoy

Department of Biomedical Informatics, Columbia University
New York, NY 10032, USA
Email: ggursoy@nygenome.org

Nicholas Tatonetti

Department of Biomedical Informatics, Columbia University
New York, NY 10032, USA
Email: nick.tatonetti@columbia.edu

Steven E. Brenner

Department of Plant & Microbial Biology, University of California, Berkeley
Berkeley, CA 94720, USA
Email: brenner@compbio.berkeley.edu

Dennis P. Wall

Department of Pediatrics (Systems Medicine), Biomedical Data Science, and Psychiatry & Behavioral
Sciences, Stanford University
Stanford, CA, 94305, USA
Email: dpwall@stanford.edu

Innovations in human-centered biomedical informatics are often developed with the eventual goal of real-world translation. While biomedical research questions are usually answered in terms of how a method performs in a particular context, we argue that it is equally important to consider and formally evaluate the ethical implications of informatics solutions. Several new research paradigms have arisen as a result of the consideration of ethical issues, including but not limited for privacy-preserving computation and fair machine learning. In the spirit of the Pacific Symposium on Biocomputing, we discuss broad and fundamental principles of ethical biomedical informatics in terms of Olelo Noeau, or Hawaiian proverbs and poetical sayings that capture Hawaiian values. While we emphasize issues related to privacy and fairness in particular, there are a multitude of facets to ethical biomedical informatics that can benefit from a critical analysis grounded in ethics.

Keywords: Ethics; Bioethics; Privacy; Fairness; Bias; Biomedical Data Science; Pono

1. Introduction

The field of biomedical informatics is intrinsically tied to ethics, as a large portion of innovations are developed for the explicit purpose of advancing human health. However, every innovation involves a wide array of stakeholders, such as clinicians, patients, family members of the patients, healthy individuals whose data are used to support an informatics solution, and many others. A solution that improves the health of one stakeholder may harm or put at risk another stakeholder in often inadvertent and subtle ways.

Considering the ethics of biomedical informatics solutions may lead to varying conclusions depending on the ethical framework used to conduct the analysis. Utilitarianism, for example, is a framework centered around doing the greatest amount of good for the largest number of people. Deontological ethics, by contrast, centers around doing the morally right action regardless of the number of people affected. One can propose countless examples of decisions that may align with one ethical theory but directly conflict with another. For example, collecting large swaths of training data that contain protected health information may be ideal from a utilitarian standpoint, as the model would be used to help a large number of people, but might be unethical from a deontological view without extensive privacy protections in place.

Here, we consider another ethical perspective: Olelo Noeau, or Native Hawaiian proverbs that capture Native Hawaiian values and the Hawaiian worldview. The Pacific Symposium on Biocomputing (PSB) takes place in Hawaii every year. As such, we center this introduction on a discussion of Native Hawaiian values as they relate to the field of biomedical informatics. While we acknowledge that many Native Hawaiian values have variety and layers to their meaning, for our purposes, we will focus on the more commonly understood meanings of these phrases. We summarize relevant Olelo Noeau for biomedical informatics in Table 1.

Table 1. Correspondence between either Olelo Noeau and analogous ethical considerations in biomedical informatics research.

Olelo Noeau	English interpretation	Relevant Hawaiian concepts, values	Analogue in Biomedical Informatics
Ike aku, ike mai, kokua aku kokua mai; pela iho la ka nohona ohana	Recognize and be recognized, help and be helped; such is family life.	Ohana, Laulima	Inclusiveness, Human-Centered Design Utilitarian ethics, Collaboration
Ike i ke au nui me ke au iki	Know the big current and the little current	Pono	Equity, Fairness
Kanukanu, huna i ka meheu, i ka maawe alanui o Kapuukolu	Covering with earth, hiding the footprints on the narrow trail of Kapuukolu	Kapu	Respect for privacy and sanctity
He waiwai nui ka lokahi	Unity is a precious possession	Lokahi	Balance of traditional performance metrics, privacy, and fairness

2. Ike aku, ike mai, kokua aku kokua mai; pela iho la ka nohona ohana. Family life requires an exchange of mutual help and recognition.

Ohana, the word for family, is one of the key Hawaiian principles that defines Hawaiian culture. The Hawaiian proverb "*Ike aku, ike mai, kokua aku, kokua mai; pela iho la ka nohona ohana*" literally describes the importance of a human-centered design process - "*recognize and be recognized, help and be helped; such is family life*" [1]. Native Hawaiian social structure is centered around extended families. For example, illnesses affect the entire Ohana because what impacts one impacts all. Laulima is also a pillar of Hawaiian culture: goals must be achieved by collaboration and cooperation. Traditionally, survival depended on this.

Following this ideal, one might suggest that biomedical informatics solutions should be developed with to work for all stakeholders, regardless of socioeconomic, demographic, political, or geographic factors. This includes involving all stakeholders in the development and design process, often with the aid of established human-centered design practices.

Digital solutions for various health conditions often and increasingly incorporate informatics solutions. For example, the SuperpowerGlass system developed by some of the authors at Stanford [2] was initially designed using in-person human-centered design sessions with participants. Before even the first quantitative feasibility study was conducted, iterative design sessions with participants were completed, and parent and child stakeholders were extensively interviewed by the study team [3-4]. Qualitative feedback was collected and coded to inform the updated design decisions of future iterations of the wearable therapeutic [5]. Only after these design sessions was the SuperpowerGlass system tested in feasibility studies [6-8] and a formal randomized controlled trial [9]. The process of co-designing with the end users of a medical solution can prevent situations where extensive time and effort is put into developing elaborate solutions that are ultimately disregarded by patients and clinicians as being unusable or unethical.

3. Ike i ke au nui me ke au iki. Know the big current and the little current.

The Hawaiian proverb "*Ike i ke au nui me ke au iki*" translates to "*know the big current and the little current*" in English, meaning that it is valuable to recognize the importance of all knowledge, be it small or large [1]. Ensuring the dialogue of data sources and data analysis is inclusive of all supports this ideal.

Similarly, the concept of Pono refers to the ideal balance of equity and abundance among all living and non-living entities [19]. A Pono concept is larger than the defense of right conduct that structures our conversations around ethics and ensures that our motivation in seeking pono is for the prosperity of all communities.

Fairness in machine learning is particularly important in the contexts of biology, medicine, and health. Machine learning models that make a diagnostic prediction, for example, can be problematic if the level of fidelity of the prediction of disease status is inconsistent across demographic groups. Machine learning classifiers are limited by the input data that are used to train them, and in many instances, the training data are unbalanced and biased. Due to differences in representation levels at the granularity of a hospital, city, or country, it may be impossible to collect balanced data sets without discarding large amounts of data from the majority class. Recent algorithmic techniques enable increased fairness, including data augmentation to upsample the underrepresented groups [10-12], enforcing a flavor of fairness in the loss function or otherwise imposing an algorithmic constraint [13-14], or post-processing methods for redefining the prediction thresholds for a black box model [15-17]. Some argue that beyond issues with data are fundamental biases in the quantitative methodologies themselves, which can put underserved populations at a disadvantage. Maggie Walter and Chris Andersen explore this topic in "Indigenous Statistics: A Quantitative Research Methodology" [18], discussing issues such as the inherent power dynamics between non-

Indigenous and Indigenous populations in statistical and policy discourse and ways that data collection methods are designed to only collect data of certain types.

4. Kanukanu, huna i ka meheu, i ka maawe alanui o Kapuukolu. Covering with earth, hiding the footprints on the narrow trail of Kapuukolu.

This Hawaiian proverb shares a value of privacy and guarding of personal information from those who pry. "In ancient times a person who did not want to be traced by his footsteps carefully eradicated them as he went" [1]. While these ideals can extend to a variety of topics in biomedical informatics, we hone in on respect of the participants whose data are used to develop biomedical innovations. We discuss respect for privacy in particular, which is the greatest concern of participants who share their data.

The concept of Kapu similarly reflects the respect required of personal data and the privilege of working with information that can be identifiable [47]. Kapu references not only the interaction with the dataset, but the ability to safeguard, protect and honor that which comprises the sacredness and dignity of each individual.

Biomedical data are sensitive by definition, often containing protected health information and identifiable information. It is crucial to share these data with the broader community in order to advance scientific progress [20-21]. However, the potential for data breaches must be accounted for. In biomedical informatics, avenues for potential breaches extend beyond traditional hacking and computer security issues. Risks specific to this field include but are not limited to identifying the genome of a single individual from within a larger dataset [22-25], cross-referencing multiple databases using demographic and familial information [26-27], inherently identifying multimedia datasets [28-32], and performing diagnostic assessments with humans in the loop [33-38]. Other considerations are the management of very small data sets, since the careless release of these could compromise not only privacy, but also dignity of subjects. Current solutions to these issues include homomorphic encryption [39-41], running privacy audits through bioinformatics tools [42-43], data sanitization [44], and differential privacy [45], and federated learning [46].

5. He waiwai nui ka lokahi; Unity is a precious possession. (Lokahi as it relates to Balance and Harmony)

Lokahi is the concept of balance; in the Native Hawaiian worldview it incorporates the balance between spirituality (Akua), humankind (Kanaka), and nature (Aina). These three pillars of Lokahi are embodied in the Lokahi triangle (Figure 1). The values of the Lokahi triangle are central to the Hawaiian notion of holistic health, including in contemporary health practices in Hawaii [48].

Lokahi is encompassed in the Hawaiian proverb "*He waiwai nui ka lokahi*", or "*unity is a precious possession*" [1]. Lokahi translates directly to ethical biomedical informatics as the marriage of traditional performance metrics (such as accuracy, mean squared error, F1-score, and AUROC) with metrics that contain an ethical component (such as attack success rate for privacy and demographic parity for fairness). Often, these metrics can be at direct odds with each other. For example, it has been repeatedly documented that improving fairness can often detriment model performance and vice versa [49-55]. Considering our framework perspective, consideration for what is ultimately the best solution for this concept is the one that does the pono (proper) thing and finds a way to balance both.
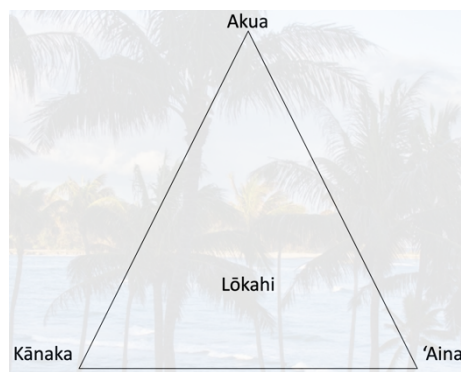

Fig. 1. Lokahi triangle, consisting of spirituality (akua), humankind (Kanaka), and nature (Aina).
Together, these elements represent balance.

6. Closing Thoughts

We emphasize that the Hawaiian cultural concepts are not simply words/phrases but ways of living. Biomedical informatics is a discipline that is inherently human-centered, and yet the quantitative logistics of the field can stray far from this central core, resulting in researchers forgetting the ethical implications of their work. We hope that this short piece will inspire PSB attendees to become Alakai, or leaders, in the incorporation of values-driven perspective in all facets of biomedical informatics research. Doing so could help avoid ethical complications and setbacks while ensuring inclusivity, respect for not only our populations but also in our field, and equity. We close with a proverb that we hope all attendees will follow: "*O ka pono ke hana ia a iho mai na lani*" [1], meaning "*continue to do good until the heavens come down to you*", or "*blessings come to those who persist in doing good.*"

7. Acknowledgements

8. Author Contributions

PYW, NP, and MK focused on the conceptual translation of these proverbs to biomedical informatics. All authors collaborated on the early stages of session design and perspective.

References

1. Pukui, Mary Kawena (editor, and translator). ʻŌlelo Noʻeau: Hawaiian Proverbs & Poetical Sayings. Bishop Museum Press, 1983.
2. Kline, Aaron, Catalin Voss, Peter Washington, Nick Haber, Hessey Schwartz, Qandeel Tariq, Terry Winograd, Carl Feinstein, and Dennis P. Wall. "Superpower glass." GetMobile: Mobile Computing and Communications 23, no. 2 (2019): 35-38.
3. Voss, Catalin, Peter Washington, Nick Haber, Aaron Kline, Jena Daniels, Azar Fazel, Titas De et al. "Superpower glass: delivering unobtrusive real-time social cues in wearable systems." In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct, pp. 1218-1226. 2016.
4. Washington, Peter, Catalin Voss, Nick Haber, Serena Tanaka, Jena Daniels, Carl Feinstein, Terry Winograd, and Dennis Wall. "A wearable social interaction aid for children with autism." In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems, pp. 2348-2354. 2016.
5. Washington, Peter, Catalin Voss, Aaron Kline, Nick Haber, Jena Daniels, Azar Fazel, Titas De, Carl Feinstein, Terry Winograd, and Dennis Wall. "SuperpowerGlass: a wearable aid for the at-home therapy of children with autism." Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies 1, no. 3 (2017): 1-22.
6. Daniels, Jena, Nick Haber, Catalin Voss, Jessey Schwartz, Serena Tamura, Azar Fazel, Aaron Kline et al. "Feasibility testing of a wearable behavioral aid for social learning in children with autism." Applied clinical informatics 9, no. 01 (2018): 129-140.
7. Daniels, Jena, Jessey N. Schwartz, Catalin Voss, Nick Haber, Azar Fazel, Aaron Kline, Peter Washington, Carl Feinstein, Terry Winograd, and Dennis P. Wall. "Exploratory study examining the at-home feasibility of a wearable tool for social-affective learning in children with autism." NPJ digital medicine 1, no. 1 (2018): 1-10.
8. Daniels, Jena, Jessey Schwartz, Nick Haber, Catalin Voss, Aaron Kline, Azar Fazel, Peter Washington et al. "5.13 Design and efficacy of a wearable device for social affective learning in children with autism." Journal of the American Academy of Child & Adolescent Psychiatry 56, no. 10 (2017): S257.

9. Voss, Catalin, Jessey Schwartz, Jena Daniels, Aaron Kline, Nick Haber, Peter Washington, Qandeel Tariq et al. "Effect of wearable digital intervention for improving socialization in children with autism spectrum disorder: a randomized clinical trial." JAMA pediatrics 173, no. 5 (2019): 446-454.

10. Pastaltzidis, Ioannis, Nikolaos Dimitriou, Katherine Quezada-Tavarez, Stergios Aidinlis, Thomas Marquenie, Agata Gurzawska, and Dimitrios Tzovaras. "Data augmentation for fairness-aware machine learning: Preventing algorithmic bias in law enforcement systems." In 2022 ACM Conference on Fairness, Accountability, and Transparency, pp. 2302-2314. 2022.

11. Sharma, Shubham, Yunfeng Zhang, Jesús M. Ríos Aliaga, Djallel Bouneffouf, Vinod Muthusamy, and Kush R. Varshney. "Data augmentation for discrimination prevention and bias disambiguation." In Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, pp. 358-364. 2020.

12. Yang, Suorong, Weikang Xiao, Mengcheng Zhang, Suhan Guo, Jian Zhao, and Furao Shen. "Image Data Augmentation for Deep Learning: A Survey." arXiv preprint arXiv:2204.08610 (2022).

13. Bellamy, Rachel KE, Kuntal Dey, Michael Hind, Samuel C. Hoffman, Stephanie Houde, Kalapriya Kannan, Pranay Lohia et al. "AI Fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias." IBM Journal of Research and Development 63, no. 4/5 (2019): 4-1.

14. Berk, Richard, Hoda Heidari, Shahin Jabbari, Matthew Joseph, Michael Kearns, Jamie Morgenstern, Seth Neel, and Aaron Roth. "A convex framework for fair regression." arXiv preprint arXiv:1706.02409 (2017).

15. Kim, Michael P., Amirata Ghorbani, and James Zou. "Multiaccuracy: Black-box post-processing for fairness in classification." In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society, pp. 247-254. 2019.

16. Lohia, Pranay K., Karthikeyan Natesan Ramamurthy, Manish Bhide, Diptikalyan Saha, Kush R. Varshney, and Ruchir Puri. "Bias mitigation post-processing for individual and group fairness." In Icassp 2019-2019 ieee international conference on acoustics, speech and signal processing (icassp), pp. 2847-2851. IEEE, 2019.

17. Petersen, Felix, Debarghya Mukherjee, Yuekai Sun, and Mikhail Yurochkin. "Post-processing for individual fairness." Advances in Neural Information Processing Systems 34 (2021): 25944-25955.

18. Walter, Maggie, and Chris Andersen. Indigenous statistics: A quantitative research methodology. Routledge, 2016.

19. Chun, Malcolm Nāea. Pono: The way of living. CRDG, 2006.

20. Arellano, April Moreno, Wenrui Dai, Shuang Wang, Xiaoqian Jiang, and Lucila Ohno-Machado. "Privacy policy and technology in biomedical data science." Annual review of biomedical data science 1 (2018): 115.

21. Knoppers, Bartha Maria, and Michael JS Beauvais. "Three decades of genetic privacy: a metaphoric journey." Human Molecular Genetics 30, no. R2 (2021): R156-R160.

22. Church, G. et al. Public access to genome-wide data: five views on balancing research with privacy and protection. PLoS Genet. 5, e1000665 (2009).

23. Homer, Nils, Szabolcs Szelinger, Margot Redman, David Duggan, Waibhav Tembe, Jill Muehling, John V. Pearson, Dietrich A. Stephan, Stanley F. Nelson, and David W. Craig. "Resolving individuals contributing trace amounts of DNA to highly complex mixtures using high-density SNP genotyping microarrays." PLoS genetics 4, no. 8 (2008): e1000167.

24. Im, Hae Kyung, Eric R. Gamazon, Dan L. Nicolae, and Nancy J. Cox. "On sharing quantitative trait GWAS results in an era of multiple-omics data and the limits of genomic privacy." The American Journal of Human Genetics 90, no. 4 (2012): 591-598.

25. Lunshof, J.E., Chadwick, R., Vorhaus, D.B. & Church, G.M. From genetic privacy to open consent. Nat. Rev. Genet. 9, 406–411 (2008).

26. Gymrek, Melissa, Amy L. McGuire, David Golan, Eran Halperin, and Yaniv Erlich. "Identifying personal genomes by surname inference." Science 339, no. 6117 (2013): 321-324.

27. Sweeney, Latanya. "Simple demographics often identify people uniquely." Health (San Francisco) 671, no. 2000 (2000): 1-34.

28. Kalantarian, Haik, Khaled Jedoui, Peter Washington, Qandeel Tariq, Kaiti Dunlap, Jessey Schwartz, and Dennis P. Wall. "Labeling images with facial emotion and the potential for pediatric healthcare." Artificial intelligence in medicine 98 (2019): 77-86.

29. Kalantarian, Haik, Peter Washington, Jessey Schwartz, Jena Daniels, Nick Haber, and Dennis P. Wall. "Guess what?." Journal of healthcare informatics research 3, no. 1 (2019): 43-66.

30. Kalantarian, Haik, Khaled Jedoui, Peter Washington, and Dennis P. Wall. "A mobile game for automatic emotion-labeling of images." IEEE transactions on games 12, no. 2 (2018): 213-218.

31. Kalantarian, Haik, Peter Washington, Jessey Schwartz, Jena Daniels, Nick Haber, and Dennis Wall. "A gamified mobile system for crowdsourcing video for autism research." In 2018 IEEE international conference on healthcare informatics (ICHI), pp. 350-352. IEEE, 2018.

32. Kalantarian, Haik, Khaled Jedoui, Kaitlyn Dunlap, Jessey Schwartz, Peter Washington, Arman Husic, Qandeel Tariq, Michael Ning, Aaron Kline, and Dennis Paul Wall. "The performance of emotion classifiers for children with parent-reported autism: quantitative feasibility study." JMIR mental health 7, no. 4 (2020): e13174.

33. Leblanc, Emilie, Peter Washington, Maya Varma, Kaitlyn Dunlap, Yordan Penev, Aaron Kline, and Dennis P. Wall. "Feature replacement methods enable reliable home video analysis for machine learning detection of autism." Scientific reports 10, no. 1 (2020): 1-11.

34. Tariq, Qandeel, Jena Daniels, Jessey Nicole Schwartz, Peter Washington, Haik Kalantarian, and Dennis Paul Wall. "Mobile detection of autism through machine learning on home video: A development and prospective validation study." PLoS medicine 15, no. 11 (2018): e1002705.

35. Washington, Peter, Emilie Leblanc, Kaitlyn Dunlap, Yordan Penev, Aaron Kline, Kelley Paskov, Min Woo Sun et al. "Precision telemedicine through crowdsourced machine learning: testing variability of crowd workers for video-based autism feature recognition." Journal of personalized medicine 10, no. 3 (2020): 86.

36. Washington, Peter, Qandeel Tariq, Emilie Leblanc, Brianna Chrisman, Kaitlyn Dunlap, Aaron Kline, Haik Kalantarian et al. "Crowdsourced privacy-preserved feature tagging of short home videos for machine learning ASD detection." Scientific reports 11, no. 1 (2021): 1-11.

37. Washington, Peter, Emilie Leblanc, Kaitlyn Dunlap, Yordan Penev, Maya Varma, Jae-Yoon Jung, Brianna Chrisman et al. "Selection of trustworthy crowd workers for telemedical diagnosis of pediatric autism spectrum disorder." In BIOCOMPUTING 2021: Proceedings of the Pacific Symposium, pp. 14-25. 2020.

38. Washington, Peter, Haik Kalantarian, Qandeel Tariq, Jessey Schwartz, Kaitlyn Dunlap, Brianna Chrisman, Maya Varma et al. "Validity of online screening for autism: crowdsourcing study comparing paid and unpaid diagnostic tasks." Journal of medical Internet research 21, no. 5 (2019): e13668.

39. Gürsoy, Gamze, Eduardo Chielle, Charlotte M. Brannon, Michail Maniatakos, and Mark Gerstein. "Privacy-preserving genotype imputation with fully homomorphic encryption." Cell Systems 13, no. 2 (2022): 173-182.

40. Sarkar, Esha, Eduardo Chielle, Gamze Gürsoy, Oleg Mazonka, Mark Gerstein, and Michail Maniatakos. "Fast and scalable private genotype imputation using machine learning and partially homomorphic encryption." IEEE Access 9 (2021): 93097-93110.

41. Sarkar, Esha, Eduardo Chielle, Gamze Gursoy, Leo Chen, Mark Gerstein, and Michail Maniatakos. "Scalable privacy-preserving cancer type prediction with homomorphic encryption." arXiv preprint arXiv:2204.05496 (2022).

42. Emani, Prashant S., Gamze Gürsoy, Andrew Miranker, and Mark B. Gerstein. "PLIGHT: A tool to assess privacy risk by inferring identifying characteristics from sparse, noisy genotypes." bioRxiv (2021).

43. Gürsoy, Gamze, Tianxiao Li, Susanna Liu, Eric Ni, Charlotte M. Brannon, and Mark B. Gerstein. "Functional genomics data: privacy risk assessment and technological mitigation." Nature Reviews Genetics 23, no. 4 (2022): 245-258.

44. Gürsoy, Gamze, Prashant Emani, Charlotte M. Brannon, Otto A. Jolanki, Arif Harmanci, J. Seth Strattan, J. Michael Cherry, Andrew D. Miranker, and Mark Gerstein. "Data sanitization to reduce private information leakage from functional genomics." Cell 183, no. 4 (2020): 905-917.

45. Dwork, Cynthia. "Differential privacy: A survey of results." In International conference on theory and applications of models of computation, pp. 1-19. Springer, Berlin, Heidelberg, 2008.

46. Khanna, Amol, Vincent Schaffer, Gamze Gürsoy, and Mark Gerstein. "Privacy-preserving Model Training for Disease Prediction Using Federated Learning with Differential Privacy." In 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 1358-1361. IEEE, 2022.

47. Chun, Malcolm Naea. No na mamo: Traditional and contemporary Hawaiian beliefs and practices. Honolulu, HI: University of Hawaii Press, 2011.

48. Chang, Healani K. "Hawaiian health practitioners in contemporary society." *Pacific Health Dialog* 8, no. 2 (2001): 260-273.

49. Calmon, Flavio, Dennis Wei, Bhanukiran Vinzamuri, Karthikeyan Natesan Ramamurthy, and Kush R. Varshney. "Optimized pre-processing for discrimination prevention." *Advances in neural information processing systems* 30 (2017).

50. Caton, Simon, and Christian Haas. "Fairness in machine learning: A survey." *arXiv preprint arXiv:2010.04053* (2020).

51. Corbett-Davies, Sam, Emma Pierson, Avi Feller, Sharad Goel, and Aziz Huq. "Algorithmic decision making and the cost of fairness." In *Proceedings of the 23rd acm sigkdd international conference on knowledge discovery and data mining*, pp. 797-806. 2017.

52. Dwork, Cynthia, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Richard Zemel. "Fairness through awareness." In *Proceedings of the 3rd innovations in theoretical computer science conference*, pp. 214-226. 2012.

53. Hardt, Moritz, Eric Price, and Nati Srebro. "Equality of opportunity in supervised learning." *Advances in neural information processing systems* 29 (2016).

54. Mehrabi, Ninareh, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. "A survey on bias and fairness in machine learning." *ACM Computing Surveys (CSUR)* 54, no. 6 (2021): 1-35.

55. Zliobaite, Indre. "On the relation between accuracy and fairness in binary classification." *arXiv preprint arXiv:1505.05723* (2015).