

1 **Increasing the presence of BIPOC researchers in computational science**

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31 **Standfirst:** *Nature Computational Science* asked a group of scientists to discuss strategies for
32 increasing the presence of Black, Indigenous, People of Color (BIPOC) researchers in
33 computational science, as well as the various considerations to be made for improving
34 education and methods design.

35
36 **Christine Yifeng Chen- Funding disparities**

37 “It’s an open secret that NSF funds Asians less.” I heard these words on a Zoom call in late
38 2020, at an informal gathering of Asian American and Pacific Islander researchers in my
39 discipline. We were meeting to support each other amidst the surge of anti-Asian sentiments
40 during the pandemic, sharing stories and exchanging advice. But this revelation about the
41 U.S. National Science Foundation (NSF) was news to me. I was a postdoc at the time, thinking
42 about my future research and future *in* research, so naturally, I was curious and concerned.

43 Seeking details, my colleague Sara Kahanamoku and I followed up with the professor who
44 made the comment. They pointed us to a little-known corner of NSF’s website that contained
45 nearly 25 years of [annual reports](#) on their merit review process and data on proposals and
46 awards. A first look confirmed our fears: for every year between 1999 and 2019, white

47 applicants received funding at above-average rates, while most other racial groups, particularly
48 Asians, were funded at below-average rates.

49 But that wasn't the whole story. Digging deeper, the funding disparities spanned all scientific
50 fields and were more pronounced for research proposals compared to those for education and
51 training. For instance, in the Directorate for Computer and Information Science and Engineering
52 in 2012–2016, research proposals by white applicants were funded at rates 1.2 and 1.5 times
53 higher than those by Asian and Black applicants. These results offer several insights, including
54 that broadening participation does not automatically lead to equitable outcomes. Asians still face
55 lower funding rates even in disciplines where Asians are well-represented.

56 While the group with the lowest funding rate varied by context, one pattern remained consistent:
57 white applicants received higher funding rates across all proposal types and disciplines.
58 Because these disparities have persisted year after year, their cumulative impact at NSF
59 amounts to billions of dollars in unbalanced funding. Similar funding advantages for white
60 applicants have also been reported at the U.S. [National Institutes of Health](#) (NIH), [NASA](#),
61 [philanthropies](#), and [other research funders in the U.K.](#), highlighting a systemic issue
62 underpinning our entire research ecosystem.

63 With the help of tenured faculty and others, we published our findings in late 2022 [1]. Our
64 publication sparked intense reactions. Of the productive responses, many asked: what's
65 causing this, and how do we fix it? There are no easy answers, but here are some observations.
66 In 2011, the NIH reported that white applicants received funding at a rate 1.7–1.8 times higher
67 than Black applicants in 2000–2006 [2]. Despite the NIH's efforts to address these gaps by
68 amassing data on possible causal mechanisms within their merit review process, the funding
69 advantage for white applicants remained unchanged at 1.7–1.8 times higher for over a decade
70 [3].

71 The unfortunate reality of these trends is that there is no "one simple fix." The hyperfocus on
72 reducing reviewer bias with double-blind or other tweaks to the review process is a textbook
73 case of costly distraction. The idea that [only active animus or unconscious bias can produce](#)
74 [racially unequal outcomes](#) in organizations is deceptive. Even if we could magically eliminate all
75 racism and bias in society, these racial funding disparities would persist. Such is the nature of
76 structural racism in contemporary contexts, where policies, processes, and social norms that
77 appear race neutral nevertheless produce and perpetuate racial inequalities.

78 In many ways, racial disparities in research funding parallel racial wealth gaps in broader
79 American society. Both gaps are widening, contrary to narratives of racial progress [4]. At NSF,
80 the funding advantage for white applicants *increased* from 1999 to 2019. The patterns are self-
81 reinforcing, a "rich-get-richer" effect where past funding success leads to future success [5].
82 Advantages start early, through prestigious graduate research fellowships [6] and [postdoc-to-](#)
83 [faculty grants](#), and compound over time, with downstream impacts on researchers' productivity,
84 recognition, and influence. Under these conditions, it is unsurprising that [decades of efforts to](#)
85 [diversify university faculty have failed](#).

86 How do we break this cycle? Simply put, to eliminate inequalities, we must address the causes
87 of inequality in the first place: unequal access to social prestige, insider knowledge, and most
88 importantly, organizational resources.

89 Follow the money.

90

91 **Alan Christoffels- Amplifying computational science research in Africa**

92 Bioinformatics and Computational Biology were formally initiated in Africa with the launch in
93 1997 of the South African National Bioinformatics Institute ([SANBI](#)) at the University of the
94 Western Cape. The following 10 years spawned a range of entities driving bioinformatics
95 activities in Africa, initially focused on human genomics. Sustained funding from the South
96 African Medical Research Council ([SAMRC](#)) established the SA bioinformatics unit and the
97 [South African Research Chairs Initiative](#) in Bioinformatics and human health. These activities
98 were expanded to genomics of vector-borne diseases through a 10-year investment in the
99 [Tropical Diseases Research program](#), and the human heredity in health ([H3Africa](#)).

100

101 These regional investments initiated and/or expanded a network of genomics and bioinformatics
102 researchers in Africa that was formalized as the African Society for Bioinformatics and
103 Computational Biology (ASBCB) in 2004. Over a period of 30 years, bioinformatics in Africa has
104 infused the biological science discipline, expanding from algorithmic development in the 1990s
105 in health sciences [7] to a range of other biological sciences from plant genomes to computer
106 aided drug discovery and many others.

107

108 As a society, we strive to support this diverse ecosystem and to contribute to shaping
109 computational skills development and fostering collaborative research opportunities both
110 regionally and abroad.

111

112 *Computational skills development*

113 Working groups within ASBCB affords members an opportunity for peer training within focused
114 community of special interest groups (COSI) including [pathogen genomics](#), [meta-omics](#),
115 [agriculture bioinformatics](#), [systems administration](#) and [structural biology](#). These forums allow
116 researchers and students to coalesce around common interests, exchange ideas, and facilitate
117 peer training. These joint initiatives have spawned [Codeathons](#) that provide a targeted approach
118 for students to apply their collective programming skills to understand the biology of model
119 organisms. For example using existing bioinformatics tools and writing code to identify SNPs in
120 drug metabolizing enzymes.

121

122 *Networking opportunity*

123 ASBCB also offers networking opportunities to identify areas of shared interest and
124 collaborations that seek to investigate locally relevant diseases. These linkages translate into
125 joint funding applications that support the growth of the research discipline. Success stories
126 include the Eastern Africa Network for Bioinformatics Training ([EANBiT](#)), a collaborative network
127 in Kenya, and Uganda supported by the Fogarty International Center of the National Institutes of
128 Health and similar networks in West Africa.

129

130 A regional affiliate of the International Society for Computational Biology ([ISCB](#)), the ASBCB
131 has co-hosted biennial ASBCB-ISCB biennial conferences since 2009. These events provide
132 the space to promote locally driven computational science research, amplify the work of young
133 African scientists, and provide a platform for scientists from diverse geographical locations to
134 exchange ideas. These events have translated into tangible student exchange opportunities for
135 exposure to interdisciplinary research environments.

136

137 *Responding to a dearth of computing infrastructure technical support*

138 The systems administration COSI has endeavored to strengthen the technical support skills
139 needed to meet the growing demands of a data intensive research environment. Over a seven-
140 year period, the Research Software and Systems Engineers ([RSSEs](#)) in Africa Forum was
141 launched. This is a discussion and networking forum for professionals involved in building
142 software and computing systems to support research on the African continent.

143
144 *Equitable access to, and development of, machine learning datasets*
145 While not formally convened as a COSI, there is growing interest among African researchers to
146 use machine learning techniques for applications in biology. The work done in natural language
147 processing provides the impetus for ASBCB to advocate for machine learning datasets
148 extended to biology. For example, despite the advances in natural language procession (NLP),
149 there remains a gap in the development of applications for African languages [8]. Access to, or
150 development of, applications for African languages create opportunities for artificial intelligence
151 (AI) application development in a wide range of domains including [healthcare](#). These efforts
152 have translated into a collection of [open-source training datasets, code and results](#) to
153 encourage growth of NLP research in African languages. Similarly, the individual efforts in Africa
154 using AI for biological applications could be strengthened by promoting these efforts via the
155 ASBCB.

156
157

158 **Roger Dube- Ongoing initiatives of AISES**

159 The fields of computational science present exciting possibilities for “Indigenous Americans”
160 (that is, American Indian, Alaska Native, Native Hawaiian, Pacific Islander, First Nation). Before
161 North American Indigenous students can benefit from these intellectual and employment
162 opportunities, there are unique challenges and disadvantages some must overcome to improve
163 the likelihood of their success.

164 These challenges include 1) overcoming inadequate preparation caused by a lack of
165 educational and technological resources (for instance high-speed internet, computers,
166 advanced STEM courses and laboratory equipment) and 2) addressing the cultural and social
167 barriers that lead students consider themselves incapable of a career in science or
168 mathematics. This limiting self-image may come from a lack of role models, knowledge of recent
169 archeological evidence of indigenous scientific and engineering achievements, culturally
170 responsive educational methods, and awareness of opportunities. There are also challenges
171 related to eliminating financial constraints, countering stereotypes and discrimination, which
172 lead to feelings of isolation that impact academic performance and mental health, and the
173 pressure of fulfilling family and community responsibilities, preventing students from attending
174 far-from-home universities.

175 I've participated in three effective approaches that can address these challenges.

176 1. Organizations such as [AISES](#) (American Indian Science and Engineering Society). This
177 national, nonprofit organization focuses on substantially increasing the representation of
178 “Indigenous Americans” in STEM studies and careers. One approach AISES uses to
179 change the perception that Indigenous Peoples have of potential and achievements in
180 STEM fields is through student poster sessions and competitions, conducted at regional
181 and national AISES meetings. There, awards are presented to reward notable
182 Indigenous accomplishments.

183

184 2. Culturally sensitive programs developed within educational institutions, such as
185 University of Manitoba's [Wawatay](#), that supports Indigenous students in their pursuit of
186 STEM degrees, thereby increasing the enrollment and retention of students from these
187 backgrounds, based on a personal communication with Dr. Carrie Selin, Academic
188 Program Lead at Wawatay. AISES is also available to guide schools in creating this type
189 of program.

190
191 3. Government-sponsored programs funding university experiences, such as the [National](#)
192 [Science Foundation's Research Experience for Undergraduates](#) (REU). These programs
193 occur during the summer, providing additional mechanisms reward Indigenous students
194 and strengthen their self-image as STEM students, and eventually professionals.

195 Although not widely known or discussed, Indigenous Americans have a long history of
196 substantial technological accomplishments, some of which were invented and in use well before
197 corresponding inventions appeared in the rest of the world. Archeology has revealed some of
198 the early inventions in the Americas such as [gold plating without the use of batteries](#) , [thirty-](#)
199 [angstrom scalpels](#), which promote quick healing of incisions, a compass [9].

200 Unfortunately, during first contact, Europeans did not recognize the effectiveness and
201 significance of Indigenous inventions and engineering solutions like those listed above. I
202 believe this occurred because of the fundamental difference between how Europeans and
203 Indigenous Americans in acquired and subsequently shared knowledge. Typically, Europeans
204 spread ideas and accomplishments through printed materials, while Indigenous cultures
205 imbedded science in their languages and taught skills and a world view through apprenticeship
206 training. Thus, Europeans dismissed the scientific and engineering capabilities that were
207 already developed and used in the Americas. This gap in the treatment and dissemination of
208 knowledge persists today, which may contribute to the dismissal of the validity of Indigenous
209 discovery and scientific practices.

210 As more students earn their degrees and assume faculty positions in STEM fields this
211 perspective will hopefully fade. Furthermore, as the number of Indigenous students, professors
212 and professionals in STEM fields grow, the process of new Indigenous STEM faculty attracting
213 more Indigenous students into STEM will become self-sustaining. Eventually there will be a
214 resurgence of the Indigenous "traditional knowledge" and approach that expands and enhances
215 western scientific methods with a more observational and holistic approach to understanding
216 complex systems. In the meantime, initiatives like those discussed here can help to close the
217 gap.

218
219 **Juan E. Gilbert- Increasing the presence of Black researchers in computational science**

220 According to the most recent Computing Research Association (CRA) [Taulbee Survey](#), there are
221 236 Black/African-American computer science (CS) PhD students enrolled in PhD programs in
222 the U.S.A., which represents 1.6% of all CS PhD students. The University of Florida's CISE
223 Department has 17 Black CS PhD students. So, roughly 7.2% of the nation's Black CS PhD
224 students are in the CISE Department at the University of Florida. Since 2006, I have produced
225 26 Black CS PhDs and currently my lab has 7 Black CS PhD students. This means that my lab
226 has produced more Black CS PhDs than most universities in their entire existence. I have

227 produced the most Black CS PhDs for any single faculty member in the country, to our
228 knowledge.

229 Over the years, increasing the presence of Black researchers in computing science research
230 has been a goal of mine and the data suggests that I have been successful in doing so.
231 Therefore, what are some of the strategic initiatives or approaches I have implemented to
232 achieve this success – I would point to two primary approaches. First, I would say that
233 representation matters. If they see it, they can be it, is something I like to say. Meaning, if you
234 want to reduce the chances of success of Black, or any group of, researchers in
235 AI/computational science, isolate them. There are too many instances where there's only 1
236 Black student in a program, or there's only 1 Black faculty member in the program. Our PhD
237 program has 17 Black students and we have 5 Black faculty members. The students clearly see
238 themselves represented in the department at all levels. Now, in cases where there are no Black
239 faculty, the students should be given access to meet Black faculty in other departments at the
240 University and at other universities. For example, the NSF Broadening Participation in
241 Computing (BPC) Alliance, Institute for [African-American Mentoring in Computing Sciences](#)
242 (iAAMCS) can connect students to a national network of Black computing researchers to
243 reduce, if not eliminate, isolation. iAAMCS has published "[The IAAMCS Guidelines for](#)
244 [Successfully Mentoring Black/African-American Computing Sciences PhD Students](#)" that
245 departments can use to learn how to best recruit, retain, and graduate Black students in
246 AI/computational science. Second, AI/computational science can be very successful at
247 recruiting Black researchers by enabling them to work on problems related to things they care
248 about. You will find Black researchers in education, health, law, and other areas that can be
249 defined as helping sciences, meaning these areas have clear connections to helping others or
250 people in the society/community. AI/computational sciences are often seen as areas that work
251 with phenomenon and artifacts and not people. If you can show how AI/computational science
252 can be used to help people, you can recruit, retain, and graduate Black researchers. It is often
253 the case, talented Black students pursue these helping disciplines, so if you can connect
254 AI/computational science to problems that relate to their communities, they will come. We have
255 been very successful in doing this by working on projects in voting technologies, law
256 enforcement, and education, to name a few. We often use culturally-relevant approaches to
257 teaching and research. We connect the life experiences of our Black students to research and
258 education in the classroom. We use examples from their communities on problems in
259 educational contexts to engage our students.

260 These strategies have been instrumental in our efforts to increase the presence of Black
261 researchers in AI/computational science research and I am confident these will work for you too.

262
263 **Sanmi Koyejo- Insights from Black in AI**

264 I vividly remember the sunny afternoon in Autumn 2015 – I was excited to give my first seminar
265 at a prestigious institution as a new postdoc. I arrived a bit too early and stood in front of the
266 room when a professor who I knew (but did not know me) popped their head in to ask if I would
267 be cleaning the room because there was a seminar starting in a few minutes. Imagine their
268 surprise when they returned later to find that I was their seminar speaker! While I have
269 experienced more or less distressing situations like this throughout my career, my colleagues
270 and friends have experienced far worse. The Black representation gap in computational science

271 is jarring and has remained as far back as I can find. According to the [Computing Research](#)
272 [Association Taulbee Survey](#), in 2023, just as in previous years, less than 2% of the PhD's in
273 computing were awarded to individuals who identify as Black. Seeing a Black scientist should
274 not be a surprise, and I believe we can work toward a time when Black computational scientists
275 are not "[rare creatures](#)".

276
277 Over the years, efforts to increase participation in computing and to normalize the presence of
278 Black scientists and practitioners have taken many forms. In 2016, we launched an initiative to
279 give this emerging community a voice, place, and professional development resources, starting
280 with the [Black in AI Workshop](#). This quickly evolved into the [Black in AI nonprofit organization](#)
281 with a mission to shift the power dynamic across the AI ecosystem and help visionaries,
282 creators, thought leaders and builders maximize the multifaceted future of artificial intelligence.
283 Black in AI has granted more than \$1 million to support some 400+ AI practitioners to be
284 present at major AI conferences. Black in AI now counts more than five thousand (5000+)
285 members – from beginners to senior professionals and academics, and has helped to prepare
286 800+ students to apply to graduate school successfully. I am honored to serve as the
287 organization's Board President alongside incredible colleagues and tireless volunteers.

288
289 As an organization, we envision a barrier-free field that empowers our community to contribute
290 and accelerate their best, most brilliant work for themselves, fellow practitioners, and their global
291 ecosystems. To this end, Black in AI implements various programs, which include: community
292 engagement, such as conferences & socials, ecosystem support, professional membership,
293 and events; programs to advance educational & career pathways, including research programs,
294 and our [Emerging Leaders in AI](#) (ELAI) graduate preparation program; and initiatives to support
295 civil society & policy, research & advocacy, and entrepreneurship innovation, which helps to
296 reduce the financial and social gaps that make it harder for Black Entrepreneurs to be
297 successful – such as our recent [whitepaper](#) for the Congressional Black Caucus on exploring
298 the impact of AI on Black Americans.

299
300 While the statistics reflect some of Black in AI's success over the years, they miss the human
301 stories of hundreds of people who have contacted me to tell me how Black in AI played a crucial
302 role in their decision to stay in the field at a time where they may have felt alone, or
303 discriminated against, or were facing some financial or knowledge gap that hindered their
304 progress. I believe we can work towards a world where an organization like Black in AI is not
305 needed, and we hope you will join us as members, allies, and partners toward a more equitable
306 future!

307

308 **Kamuela Enos, Kari Noe, Jason Leigh - Importance of co-designing tech with the**
309 **community**

310 The first key component for any technology, whether developed or not, to empower Indigenous
311 communities is equity. By equity, we refer not to the DEI (Diversity, Equity, Inclusion) sense of
312 inclusion, but rather the legal sense of co-production and co-ownership. While focusing on the
313 inclusion of Indigenous people due to historic injustices is important, it still often aligns with
314 colonial systems and structures. A more meaningful approach is to recognize the value of

315 Indigenous practices to contemporary society for their deep, localized insights. Ancestral
316 knowledge represents thousands of years of optimizing natural systems within regenerative
317 frameworks.

318

319 The second component is ensuring that Indigenous communities, who hold this knowledge,
320 have the opportunity to own and co-produce technology. The primary goal here is to sustain
321 ancestral practices for current and future generations within their own communities. Innovations
322 from research initiatives should enhance existing systems of ancestral practice rather than
323 disrupt them. While ancestral practices can evolve, they must remain foundational to the
324 development and implementation of new technologies. For example, when a contemporary R1
325 University adopts that mindset that traditional practices are actually sciences, and that the
326 indigenous communities that hold these practices are ecosystems of innovation, then the whole
327 engagement framework changes. In this ideal mode of engagement, the community is not
328 sharing their knowledge with a researcher to help forward the research interests of the
329 university/academy. Instead, the research unit understands that the community's work of
330 restoration is vital to regional societal well-being, so it orients its research to support community
331 agency and continuity. In this model, the community transitions from a thing to be studied, to
332 becoming a consultant to help society restore biocentric practices whose viability have lasted
333 centuries.

334

335 This orientation supports communities and their experts in evaluating contemporary
336 technologies to achieve ancestral outcomes. Adopting this approach can provide solutions to
337 complex societal issues that benefit both Indigenous and broader communities. The ultimate
338 goal is for these communities to be recognized as ecosystems of innovation for societal well-
339 being, provided that appropriate political and economic infrastructures are established to
340 support their practices.

341

342 For example, in visualizing climate data in our National Science Foundation funded
343 [Change\(Hawai'i\) EPSCoR project](#), our approach goes beyond creating a functional visualization
344 system. We adopt a holistic design framework that incorporates thoughtfulness and equity
345 throughout the process, from creation to implementation and sustainable use [10]. This means
346 not only co-designing the technology with community members but also integrating their
347 practices of biocultural restoration and ancestral sciences. Our goal is to prioritize ancestral
348 observational methodologies alongside other critical mapping components. This approach
349 empowers communities whose ancestral data is often excluded from large-scale decision-
350 making processes or extracted without consent.

351

352 The end goal is to re-normalize Indigenous practices, input, and agency in the development and
353 implementation of technology, not merely as a DEI initiative. By doing so, these highly refined
354 projects can be supported with community ownership and provided with the resources needed
355 to sustain their use.

356

357 **Carlo Liquido, Amy McKee- Towards Kanaka-centric design**

358 As user experience (UX) designers who grew up in Hawai'i, we have struggled with reconciling
359 the cultural differences between capitalistic design practices in the “real world” and the
360 community-centered values we learned as children. The idea that we should design products
361 and tools meant to extract maximum profit from people and communities felt foreign to us.

362 While telling a story one day, we began to imagine a different way that we could approach
363 designing digital products and services, and we looked for guidance and inspiration from
364 Indigenous texts and stories (mo'olelo). One term that resonated with us was "Indigenous
365 resurgence," which offers an affirmative and abundance-based lens of reclaiming ancestral
366 knowledge ('ike kupuna) and designing solutions. This concept provided us with the theoretical
367 framework to move our design thinking from a capitalist and colonial paradigm towards a
368 kanaka-centered one.

369 In Hawaiian, [kanaka](#) means "human" or "people". While the word "kanaka" is often used to refer
370 specifically to Native Hawaiians (such as, Kanaka Maoli or Kanaka 'Ōiwi), many old Hawaiian
371 newspapers of the 1800s used the word "kanaka" inclusively to describe people from all around
372 the world (for instance, Kanaka Haole meant white person, Kanaka Kepani meant Japanese
373 person, [etc.](#)). This broader, inclusive interpretation of "kanaka" aligns with the story of the first
374 kanaka, [Hāloa](#). The story of Hāloa illustrates the familial and interdependent relationship
375 between humans and non-humans, where the land, plants, animals, and other phenomena are
376 our elder siblings and we must care for the earth as the younger sibling.

377 Our goal in creating the term, "Kanaka-Centered Design", is not to "Hawaiianize" Human-
378 Centered Design, but to respectfully reclaim and assert a design practice rooted in 'ike kupuna
379 (ancestral knowledge). This approach embodies a deep sense of responsibility and ethics
380 rooted in Hawaiian culture and sovereignty, and is inclusive of all beings, including past
381 (kupuna), present (kanaka), and future generations (mo'opuna).

382 In essence, Kanaka-Centered Design embraces creating impactful solutions, rather than the
383 relentless need to scale. It centers people and the planet, not profit. It designs for the reciprocal
384 and regenerative, not for the extractive. It designs for future generations, not for the fleeting
385 trends of the market.

386 Organizations like [Nalukai](#) and ['Āinaquest](#) embody Kanaka-Centered Design by shifting the
387 focus from a "designer versus user" mentality to one of community empowerment. Nalukai
388 mitigates the issue of savior-driven problem solving by reframing problems as "kuleana," which
389 focuses on the privilege and responsibility to serve one's community, thus eliminating the
390 distinction between the designer and the user. 'Āinaquest is an educational card game that
391 challenges the community to cultivate native and canoe plants in order to deepen their collective
392 pilina (relationships) with the land. This emphasis on reciprocity and shared responsibility
393 resonates deeply with 'ike kupuna, as exemplified in the design of loko i'a (fishponds), which are
394 complex aquaculture systems. The design of loko i'a demonstrates a deep understanding of
395 ecological balance and a commitment to long-term sustainability. By working in harmony with
396 natural systems, rather than exploiting them, loko i'a provided abundance for generations,
397 showcasing the wisdom and ingenuity of ancestral knowledge.

398 Kanaka-Centered Design also champions excellence, recognizing the inherent gifts within
399 individuals and communities, and fostering their development. In Hawai'i, we have experienced
400 and witnessed the detrimental effects of settler colonialism, which often imposes low
401 expectations on our youth and limits their potential. As designers, we echo Queen Kapi'olani's
402 call to "Kūlia i ka nu'u –strive for the highest," and not only empower individuals to reach their
403 full potential, but also provide the resources to nurture new talent. This is exemplified in the
404 work of [Pi'ikū Co.](#), which empowers aspiring web designers in Hawai'i by providing resources,
405 training, mentorship, and compensation—all the tools necessary for new talent to thrive. This not

406 only nurtures new talent but also creates opportunities for excellence by challenging interns to
407 solve real-world problems that directly affect their community.

408 In conclusion, Kanaka-Centered Design provides us a way to decolonize our UX methodology
409 and encode ancestral knowledge into our designs. It is our way of recognizing that the future of
410 our planet depends on designers who think holistically, sustainably, and inclusively of human
411 and non-humans, and of past (kupuna), present (kanaka), and future generations (mo'opuna).

412

413 **Tai-Quan Peng- From promise to practice: Overcoming barriers in computational**
414 **communication research in the Asia-Pacific region through AI**

415 Computational methods have been heralded as a transformative force in communication
416 research, promising new insights and methodological advancements [11]. However, the
417 expected revolution in the Asia-Pacific region has yet to fully materialize. Computational
418 communication studies are predominantly conducted by scholars from well-represented, often
419 Western, societies. This has resulted in a lack of attention to under-represented communities
420 within the Asia-Pacific region, where unique cultural, linguistic, and social dynamics offer rich
421 research opportunities.

422 The limited adoption of computational methods in these regions can be attributed to several key
423 challenges. For instance, the technical resources and education for computational research, to
424 provide expertise in programming and data analysis, may be beyond the reach of many
425 scholars in underdeveloped areas. Additionally, the linguistic diversity of the Asia-Pacific region
426 presents a formidable barrier [12]. To date, many natural language processing tools are
427 developed for Western languages, requiring extensive customization to be applicable in local
428 contexts. This adaptation process is both time-consuming and costly, further deterring
429 researchers from utilizing these methods. Moreover, the high costs associated with developing
430 and maintaining the necessary computational infrastructure pose a substantial financial
431 obstacle. This financial barrier exacerbates the digital divide, leaving many researchers unable
432 to contribute to or benefit from advancements in computational methods.

433 To address these disparities, leveraging current AI technologies, particularly large language
434 models (LLMs), offers a promising solution. LLMs can substantially lower the technical barriers
435 by providing user-friendly interfaces for data analysis and natural language processing tasks,
436 making these tools more accessible to scholars without advanced technical training.
437 Additionally, LLMs are increasingly capable of handling linguistic diversity, allowing for more
438 accurate analysis of texts in various local languages. The decreasing cost of deploying AI
439 technologies also makes it more feasible for researchers to use these powerful tools with less
440 financial burden. By integrating LLMs into their research, scholars in the Asia-Pacific may be
441 able to overcome many of the current obstacles, fostering a more inclusive and comprehensive
442 understanding of communication phenomena in the region.

443 LLMs can capture the rich tapestry of languages and dialects of the region, enabling
444 researchers to conduct cross-linguistic studies with greater ease. This capability helps break
445 down language barriers, ensuring that research is inclusive and representative of the region's
446 diverse population.

447 Moreover, LLMs can also potentially enhance the testing of various interventions. That is, by
448 carefully controlling the inputs through appropriate prompts and training data, LLMs can
449 simulate the impact of different measures aimed at promoting innovative ideas and
450 technologies, altering health behaviors, or implementing new policies. This control allows
451 researchers to test various scenarios and predict outcomes with high accuracy before
452 implementing interventions on a larger scale. In regions like the Asia-Pacific, where socio-
453 political contexts vary widely, such controlled simulations provide critical insights, enabling more
454 informed and tailored decision-making.

455 Despite its potential, the application of AI in computational communication research in the Asia-
456 Pacific region is not without limitations. One major concern is the bias inherent in AI models,
457 often skewed toward WEIRD (Western, Educated, Industrialized, Rich, and Democratic)
458 populations [13]. This bias arises from inadequate data representing the cultural and linguistic
459 heterogeneity of the Asia-Pacific region, leading to models that may not accurately reflect local
460 nuances. Additionally, the absence of comprehensive “ground truth” datasets complicates the
461 validation of AI performance, risking erroneous conclusions. If AI models continue to be trained
462 predominantly on data from WEIRD populations, they may perpetuate existing biases and fail to
463 address the unique challenges of the Asia-Pacific region. Ensuring that AI tools are developed
464 and validated using diverse datasets is crucial to prevent this outcome. Furthermore, the
465 persistent insufficiency of infrastructure that impedes the development of computational
466 communication research also hampers the effective deployment of AI technologies in the Asia-
467 Pacific region, posing significant challenges to fully leveraging AI’s potential.

468

469 **Karaitiana Taiuru- Treatment of Māori language in language modeling**

470 The Māori language was banned by native schools and other government led assimilation
471 practices in the late 18th century, so effectively, that by 1980 we had less than 20% of native
472 speakers nationwide, and within my own tribe we had 3 native speakers. Tribal dialects were
473 also replaced with one standard version of Māori, influenced by the introduction of the written
474 Bible and by ethnographers who chose to ignore the rich and diverse tribal dialects throughout
475 our country in favor of a standard dialect. Large Language Models (LLMs) have the ability to
476 revitalize dialects, it is not likely a preference for Māori as it is a local distinguishing treasure that
477 is used by tribal members in physically meetings of cultural significance.

478

479 Community activism throughout the late 1970’s and the establishment of language training for
480 preschoolers and other educational facilities led to the Māori language being recognized as an
481 official language in 1987. The key lessons learned for Māori was that the language had to be
482 normalized in our lives and society, and then to be spoken by at least three generations within
483 one family in order to be preserved. We have now reached that lofty dream, but moving forward
484 we need to address the controversial topic of LLMs that are widely used and that already
485 incorporate our language.

486

487 The Māori language has a substantial amount of digitized online resources such as [legal](#)
488 [records](#), [parliamentary corpus](#), [journals](#), [newspapers](#), [archives](#) and [audio-visual materials](#), and
489 with tens of thousands of new words created to [accommodate the translation](#) of products such
490 as Microsoft Office, Windows, and Google. Google had a Māori software engineer contribute to
491 and help develop [Google Translate for Māori](#). This has generated a huge amount of data for
492 artificial intelligence (AI) to incorporate the Māori language and for it to be used relatively well.

493 For instance, ChatGPT already speaks Māori at a reasonable level of accuracy. I estimate that
494 in less than two years it will be as fluent and accurate as a Māori language expert.

495
496 A recent spike with people wanting to learn the Māori language has resulted in a demand issue
497 for teachers that far outweighs the supply. This has led to a large uptake of learners of Māori.
498 language using LLM's as both a supplementary tool and an alternative method to learn Māori.
499 Still, many dangers exist. For example, we provide AI technologies with our sacred rituals and
500 esoteric knowledge, our language and history will not be our own and risks being
501 commercialized and changed by international corporations. As Māori, we need to revisit our
502 traditions, go back to our tribal lands and re-engage with elders and tribal members to learn the
503 sacred aspect of our language and ensure that those aspects remain in our human world and in
504 our tribal homes and lands. LLM developers can assist in this area by acknowledging copyright
505 in source data and being transparent about data sources.

506
507 Other risks include misogynist ethnographers' historical texts being used to train some LLMs,
508 resulting in incorrect statements about Māori, written in the Māori language. This is
509 predominantly with our creation stories and historical knowledge, where the Māori translated
510 King James Bible is being offered as Māori creation stories and the LLMs are mixing and
511 matching tribal stories to create new ones.

512
513 Another emerging risk is phishing attacks or identity theft, as spammers are using LLMs to
514 correspond with Māori and it's becoming more difficult to discern real from fake. Previously,
515 Google Translate often made mistakes when translating, making it easier to identify. LLM
516 developers should consider how best to prevent their tools being used in phishing, bullying and
517 other common forms of online scams and bullying. Moving forward, we hope that LLMs are key
518 to the long-term revitalization and normalization of the Māori language.

519

520 **Competing Interests**

521 The authors declare no competing interests.

522

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572 This work was performed under the auspices of the U.S. Department of Energy by
573 Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344 (LLNL-
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