Hawai‘i Journal of Health & Social Welfare

A Journal of Pacific Health & Social Welfare

January 2026, Volume 85, No. 1, ISSN 2641-5216

Hawai‘i Journal of Health & Social Welfare

ISSN 2641-5216 (Print), ISSN 2641-5224 (Online)

Aim:
The aim of the Hawai‘i Journal of Health & Social Welfare is to advance knowledge about health and social welfare, with a focus on the diverse peoples and unique environments of Hawai‘i and the Pacific region.

History:
In 1941, a journal then called The Hawai‘i Medical Journal was founded by the Hawai‘i Medical Association (HMA). The HMA had been incorporated in 1856 under the Hawaiian monarchy. In 2008, a separate journal called the Hawai‘i Journal of Public Health was established by a collaborative effort between the Hawai‘i State Department of Health and the University of Hawai‘i at Mānoa Office of Public Health Studies. In 2012, these two journals merged to form the Hawai‘i Journal of Medicine & Public Health, and this journal continued to be supported by the Hawai‘i State Department of Health and the John A. Burns School of Medicine.

In 2018, the number of partners providing financial backing for the journal expanded, and to reflect this expansion the name of the journal was changed in 2019 to the Hawai‘i Journal of Health & Social Welfare. The lead academic partners are now the six units of the UH College of Health Sciences and Social Welfare, including the John A. Burns School of Medicine, Office of Public Health Studies, the Thompson School of Social Work & Public Health, the School of Nursing and Dental Hygiene, the UH Cancer Center, and the Daniel K. Inouye College of Pharmacy. Other partners are the Hawai‘i State Department of Health and the UH Office of the Vice Chancellor for Research. The journal is fiscally managed by University Health Partners of Hawai‘i.

The HJH&SW Today:
The Hawai‘i Journal of Health & Social Welfare is a monthly peer-reviewed journal. Full-text articles are available on PubMed Central. The HJH&SW cannot be held responsible for opinions expressed in papers, discussion, communications, or advertisements. The right is reserved to reject editorial and advertising materials that are submitted. Print subscriptions are available for an annual fee of $250. Please contact the journal for information about subscriptions for locations outside of the US.

The HJH&SW is financially supported by the academic units within the UH College of Health Sciences and Social Welfare, the UH Office of the Vice Chancellor for Research, the Hawai‘i State Department of Health, and by advertising. However, the journal’s editorial board maintains editorial independence from these entities for the acceptance and publication of research articles. All editorial decisions regarding the selection and editing of research articles are made by the members of the journal’s editorial board. The decisions of the editorial board are not influenced by nor subject to the approval of these entities.

The aim of the columns of the HJH&SW is to provide a space for the entities that financially support the HJH&SW to diseminate information regarding their research, programs, goals, or current issues facing their respective fields. Columns are edited by the HJH&SW contributing editors, who are employees of the agencies that sup- port the HJH&SW.

Journal Contact Information:

Mailing Address: Hawai‘i Journal of Health & Social Welfare
University of Hawai‘i at Mānoa
Thompson School of Social Work & Public Health
2430 Campus Road, Gartley Hall
Honolulu, Hawai‘i 96822

Website: http://hawaiijournalhealth.org/

Email: hjhsw@hawaii.edu

Historical Review of Acute Myocardial Ischemia Risk Assessment

Jerris R Hedges, MD, MS, MMM[1], W Brian Gibler, MD[2], Gary P Young, MD[3,4]

[1] Department of Surgery, University of Hawai'i at Mānoa, John A Burns School of Medicine, [2] Department of Emergency Medicine, University of Cincinnati College of Medicine, [3] Department of Emergency Medicine, Oregon Health & Science University, [4] Department of Emergency Medicine, Highland Hospital/Alameda County Medical Center

Keywords: Myocardial Ischemia, Myocardial Infarction, Acute Coronary Syndrome, Chest Pain, Cardiac Biomarkers, Troponin, Creatine Kinase Myocardial Band (CKMB), Electrocardiogram, Chest Discomfort

https://doi.org/10.62547/JMJM6124

Abstract

The specialty of emergency medicine has emphasized the importance of the rapid diagnosis and treatment of time-dependent conditions. Recognition of the emergency patient at high risk for myocardial ischemia is one such condition. In collaboration with cardiologists and laboratory medicine specialists, emergency physicians have revolutionized the approach to diagnosing patients at risk for myocardial ischemia in the emergency department. This article provides a historical viewpoint based upon the authors' practice and research in myocardial ischemia risk recognition beginning in the 1980s, along with the work of selected researchers in the field to describe an evolving understanding of the underlying pathophysiology, the application of serial laboratory diagnostic techniques, and resultant goal-directed multidisciplinary care of the at-risk patient. Such an approach lends itself to the clinical assessment of patients in a multicultural, multiethnic environment as seen in Hawai'i. The evolution of acute myocardial ischemia risk assessment through emergency medicine research is detailed, including (a) the recognition of the limitations of patient discomfort subjective language descriptors, (b) the incorporation of highly specific and sensitive laboratory biomarkers for MI, and (c) the use of mechanistically-driven, serial clinical and laboratory assessments. Today's objective emergency approach to acute myocardial ischemia risk assessment is relevant to cross-cultural applications, as is required for medical care in the Pacific Basin.

Abbreviations

CCU = coronary care unit
CPC = chest pain center
CKMB = creatinine kinase myocardial band
ECG = electrocardiogram
ED = emergency department
MI = myocardial ischemia

Introduction

> "Initially it seems silly, then it seems controversial, then it seems progressive, and then it seems obvious."
> *James Colgrove, Dean of the Postbaccalaureate Premedical Program, Columbia University, as cited by Sandro Galea, Dean of Public Health, Washington University in St. Louis, MO.*

This quote is a reminder that the scientific basis of medical practice is always evolving. It also reminds us that the birth of new knowledge or clinical approaches is often painful and prolonged. In the mid-1970s and early 1980s, the rapid diagnosis and/or treatment of time-dependent conditions was the rallying cry of the new and evolving discipline of emergency medicine. Scientific advancement was achieved in part through the adoption and adaptation of new technologies for those purposes and in part through collaborations with other established disciplines which allowed the co-evolution of these medical disciplines and their shared patient care responsibilities. This article provides a historical viewpoint of the professional and clinical synergy which evolved into the modern recognition of ischemic heart disease and its early treatment. As myocardial ischemia and myocardial infarction represent a continuum of injury to myocardial cells, this historical article treats these diagnoses as part of a unified myocardial ischemia (MI) risk assessment.

In the 1970s, the triggering mechanism of MI was unclear. Although some pathologists had commented on thrombi found occluding coronary vessels post-mortem, it was unclear whether the thrombi initiated the myocardial damage by compromising blood flow or if the thrombi resulted from limited blood flow around the time of death.[1,2] A common belief was that MI followed progressive coronary atherosclerosis compounded by an oxygen delivery supply and demand imbalance. This is now known as Type 2 MI.[3]

In the early 1980s, closer pathological examination of post-mortem coronary arteries led to a more nuanced understanding of MI.[4,5] That is, acute inflammation following the rupture of a cholesterol plaque commonly leads to progressive thrombotic coronary artery occlusion with MI. Thus, it became recognized that the more common initiating factor leading to MI is a fresh coronary artery thrombus causing ischemia, known as Type 1 MI, rather than an oxygen delivery supply/demand imbalance with a fixed coronary occlusion as in Type 2 MI.

In the mid-1980s, interventional cardiology became a viable means of treating patients with evolving MI. Interventional cardiologists quickly became some of the emergency physicians' strongest allies. Where the prior role of cardiologists had largely been to diagnose MI in the hospital and to recommend medical interventions reducing oxygen demand, the interventional cardiologists now focused on locating specific areas of coronary occlusion and providing reperfusion interventions for the myocardium.[6] The evolution of more rapid and sensitive approaches to recognizing MI in the emergency department (ED) provided the

means for these cardiologists to focus their efforts on preserving heart tissue rather than supporting a severely damaged heart.

Patients' recovery post-intervention depended on rapid reperfusion of compromised myocardium thus minimizing permanent muscle loss. This evolving understanding of the time-dependent reversibility of MI, and the associated reduction in the risk of clinical complications, was coupled with a closer look at the presentation of the patient with potential MI and the decision-making associated with patient hospital admission.

Methods

This article chronicles advances in ED approaches to recognizing patients at risk for MI beginning in the 1980s. Contextual commentary based upon the authors' own research will reflect the growing awareness of the underlying pathophysiology of MI, the application of serial laboratory diagnostic techniques and ED assessments, and resultant goal-directed multidisciplinary patient care. This historical viewpoint highlights the evolution of emergency care through research based in a newly emerging discipline. Representative articles were selected to denote key inflections in understanding and practice. The importance of such an approach to ED risk assessment in a multicultural, multiethnic environment is emphasized.

Early limitations of MI risk assessment

The process of determining which chest discomfort patients should be admitted from the ED to the hospital or coronary care unit (CCU) was not standardized in the 1980s. The symptoms associated with MI can be variable, especially in women.[7,8] The capacity to admit and evaluate people at risk is limited at any hospital due to a scarcity of CCU beds, nurses, and cardiologists. In the 1980s, the patient's electrocardiogram (ECG), physical exam, and clinical history were the tools available to determine an ED patient's risk for MI and death. A patient with chest discomfort showing ECG abnormalities such as ST-segment elevation or a new left bundle branch block was deemed to be a high-risk patient and quickly admitted to a CCU. As coronary intervention in the cardiac catheterization laboratory became more available in the late 1980s, these higher risk patients were often taken directly from the ED to an interventional cardiac catheterization laboratory. However, not all patients with an MI present to the ED with these dramatic ECG findings.

Population-based studies determined that most ED patients with chest discomfort did not have MI or some other life-threatening condition.[9] Those with an evolving MI were not always obvious using available tests. In one study of ED patients of all ages determined to have an evolving MI, about 2% had initially normal or minimal ECG findings.[10] In an elderly, largely male chest discomfort population with an initially normal or minimal ECG findings, 9%-13% were having an evolving MI.[11] Other studies found that prior to the incorporation of serial cardiac biomarker tests, approximately 2-5% of ED patients with an evolving MI were unrecognized as being at high risk and were sent home.[12,13] One study reported death in 25% of MI patients released home from the ED.[13]

In the mid-1980s, a predominately Boston-based multihospital study of ED patients with chest discomfort was launched with a plan to use statistical analysis of comprehensive patient demographic and past medical history (eg, age, sex, history of risk factors for MI), patient descriptors of their discomfort (eg, location and character of the discomfort), other symptoms (eg, shortness of breath, fatigue, indigestion), and the initial ECG to predict which patients were truly at high risk and warranted CCU admission, versus admission to a regular hospital bed, or, sent home.[14] The Cincinnati collaborating group in the multi-site study appreciated the use of a standardized approach to evaluating chest discomfort patients. The Cincinnati investigators concurred that the study algorithm helped risk stratify such patients for placement within the hospital, but were concerned that the study's algorithm did not help emergency physicians with their most difficult decision, identifying the MI patient at risk for release home from the ED. The multi-site algorithm emphasized the patient's description of chest discomfort, but the Cincinnati collaborators (including 2 of the authors – JRH and WGB) observed differences in the regional, demographic, and cultural use of verbal descriptors for chest discomfort. For example, patients in Cincinnati would often use "sharp" to describe the severity of their chest discomfort whereas patients in Boston would use "sharp" to describe the brief, knife-like character of their discomfort. Any diagnostic algorithm generated using such verbal descriptors of discomfort was likely to be flawed for ED risk stratification given the variable use of verbal descriptors by patients. Such an approach to improve clinical diagnostic skills using subjective descriptors of chest discomfort is of uncertain value given different regional and cultural influences on language.[15] Similarly, the algorithm heavily relied on ECG abnormalities and would miss an evolving MI in patients with normal or subtle ECG findings.

At Cincinnati, the assessment of ED chest discomfort patients to improve MI recognition was thus modified. Because the diagnosis of MI in patients after admission to the hospital depended upon serial measurement of ECGs and cardiac biomarkers (eg, creatinine kinase myocardial band or CKMB), the Cincinnati investigators advocated for using these measurements in the ED. The team postulated that patients at risk for MI could be identified by using a cardiac biomarker blood test in the ED as an exit screen especially in patients who might otherwise be released home. This approach was highly criticized because a single test might be falsely negative and theoretically lead physicians to send an MI patient home.[16]

False negative single test results could occur due to the time-dependent nature of muscle tissue breakdown or could reflect the dynamic process of the development of a thrombus (from a ruptured atherosclerotic plaque) with a varying degree of coronary artery occlusion. The variable uptake of released cardiac markers into the blood stream may introduce additional delay. For this reason, admitted

patients in the 1980s had serial measurements done over multiple days before a diagnosis of MI was established or excluded.

In Cincinnati, an ED-based follow-up clinic was established to repeat initially nondiagnostic ECGs in patients who had been clinically diagnosed as low risk for MI and who had been released home after their ED evaluation.[17] To improve diagnostic accuracy, CKMB blood tests were obtained on these ED patients. The initial ED-drawn blood test, and a follow-up clinic blood test obtained within 48 hours of the initial evaluation were analyzed during the follow-up clinic visit. Through this clinic, MI patients were identified who had initially been released home with a presumed low risk condition.[12] Fortunately, no major complications occurred at home and the rate of compliance with early follow-up using the dedicated ED clinic was significantly improved over a larger historical population sent home without structured short-term follow-up.[18]

Subsequently patients scheduled for discharge home were kept in the ED for serial cardiac biomarker testing rather than taking the risk of sending the patient home. The patients had nursing and physician oversight comparable to a hospital CCU, and had their serial tests done over a shortened period of 1-2 days compared to 3-5 days in the CCU. Using cardiac biomarker testing, serial ECGs, and provocative stress testing, further reduced the time frame for evaluation. This approach led to better use of CCU admissions for high-risk patients, ie, patients with an abnormal ECG or with positive cardiac biomarkers while under observation in the ED.

Socializing practice change

These concepts are now standard practice in ED care internationally but were not immediately accepted. The suggestion that unrecognized MI patients might be identified with an exit screening cardiac biomarker test in the ED was challenged.[9,16] The early cardiac biomarker tests used, although more sensitive and specific than the gel electrophoresis tests available at the time in other hospitals, were less sensitive than today's biomarkers.

Over time, the biotechnology and laboratory medicine fields developed more accurate cardiac biomarker assays. While focused on MI detection, biomarkers also were assessed for prediction of MI complications and death.[19,20] Ongoing research evaluated the test performance of more accurate immunoassay detection systems. One evaluated biomarker that is now generally used in the ED is the troponin biomarker test.[21] Such tests have been found effective with multiple ethnic groups internationally.

Initially, physicians were not comfortable with using these tests for ED decision-making.[16,22] Risk stratification of ED patients requires the integration of these tests with patient clinical information, symptoms (eg, shortness of breath, fatigue, indigestion), and the initial ECG. Thus, a series of ED chest discomfort patient risk stratification studies wherein the relative impact of the initial biomarker test results on clinical decision making during actual clinical care were initiated.

In a Portland-based pilot study, an initially negative cardiac biomarker test did not eliminate the physician's concern for MI when other historical and ECG findings were abnormal.[23] Rather, the test appropriately raised the suspicion for MI when the result was positive and the patient had an otherwise unremarkable presentation. In a follow-up multicenter study of real-time decision making, emergency physicians were asked to state their planned disposition before and after being given cardiac enzyme test results. No patient slated for admission was released after a negative enzyme test, however 4% of subsequently diagnosed MI patients had been selected by the treating physicians for release home from the ED before the test results became known.[24] The admission decision for these subtle MI patients was changed by the abnormal CKMB test result. Thus, clinical decision-making was enhanced by an initially positive test but not compromised by an initially negative test.

In multicenter studies in Cincinnati, Portland, Nashville, and elsewhere, more was learned about the temporal nature of cardiac biomarker rise, allowing a more sophisticated application using ED-based serial biomarker results in ED clinical decision making.[25-29] For example, a patient with a small MI may have a paradoxically earlier rise in their biomarker, due to earlier biomarker entry into the blood stream. Conversely, a large area of myocardial damage could have a slower uptake of the cardiac biomarkers into the circulation as previously noted in admitted patients.[30]

Unfortunately, the precise time of ischemia onset with an MI is not always possible to determine[7,31] and although the probability of an abnormal cardiac biomarker increases with a longer duration from the MI onset until blood sampling, some patients may have an abnormal cardiac biomarker level upon initial presentation and others may take hours to surpass a general population normal level. Of additional concern was the observation that patients with a small heart size (associated with smaller body mass) may have a small MI which never surpasses a general population normal upper limit value for a cardiac biomarker test.

More recent studies using a very sensitive troponin biomarker and measuring a significant change from baseline rather than requiring the biomarker to reach a specific, abnormal threshold, suggest that shorter time intervals in serial testing may be adequate for ED risk stratification.[32, 33] That is, the relative change in an individual's biomarker level over a few hours is more important than reaching some absolute level of the biomarker that is based upon large population studies.[21] Thus, personalized biomarker risk stratification strategies are useful when looking for early signs of MI.

Current clinical ischemia recognition

Internationally, emergency physicians have incorporated cardiac biomarker use – including sequential cardiac biomarker measurement when the initial test is negative - in their evaluation of ED patients with chest discomfort. All chest discomfort patients warrant an initial ECG to assess for a major coronary artery occlusion requiring direct ED-

to-cardiac catheter laboratory transfer for care. However, for patients without dramatic ECG changes, the greater value of serial cardiac biomarkers over serial ECGs for prediction of complications and need for cardiac interventions was demonstrated by investigative teams more than 3 decades ago.[11,19,20]

ED Chest Pain Centers (CPCs) developed by emergency physicians in collaboration with cardiologists are commonly used to evaluate patients with possible MI. Using serial cardiac biomarker testing, serial ECGs, and graded exercise testing to detect cardiac heart cell death, ischemia at rest, and exercise-induced ischemia, physicians have improved the sensitivity for detecting patients in the ED at risk for MI.[34-38] The evaluation of patients in ED CPCs in the 1990s proved to be a clinically efficacious and a cost-effective approach to the care of chest discomfort patients.[39, 40] National patient care guidelines for the evaluation and treatment of ED chest discomfort patients adopted this collaborative approach to more rapidly detect MI.[39,41]

Although time-dependent cardiac ischemia is better understood, recognized and managed, a recent editorial suggested that this approach may lead to the "over-diagnosis" of Type 1 myocardial infarction.[42] Since patients with elevated cardiac biomarkers have greater risk for heart failure and sudden death,[19,20] and because Type 2 MI continues to represent a diagnostic and therapeutic challenge warranting attention,[3] such concern for "over-diagnosis" of Type 1 MI will require cautious prospective assessment, as the emergency evaluation of chest discomfort patients evolves.

Conclusion

This article emphasizes the historical progression of scientific knowledge and clinical practice in parallel with the evolution of emergency medicine and interventional cardiology as clinical disciplines. Through this change in practice, the recognition and care of patients with risk for MI complications has significantly improved in large part through the incorporation of cardiac biomarkers in emergency practice. This approach backstops culturally determined language cues and is thus especially relevant in Hawai'i. Although the use of cardiac biomarkers in the ED was initially rejected, this approach is now considered a diagnostic standard of care. Thus, James Colgrove's quote might be restated as follows:

Advances in diagnosis and therapy occur through paradigm shifts - based upon scientific evidence and medical debate – this approach will continue to guide future care evolution.

Acknowledgement

This historical narrative chronicling the advancement of the ED approach to MI risk assessment was presented at the May 2024 Edinburgh Combined UK-US Emergency Medicine Research Reunion, Royal College of Surgeons, Edinburgh, Scotland, UK.

None of the authors have a conflict of interest with a commercial entity related to this historical review. This work was supported in part by grant number U54 MD007601 from the National Institute on Minority Health and Health Disparities. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Submitted: September 16, 2024 PST. Accepted: November 11, 2025 PST. Published: January 01, 2026 PST.

References

1. Roberts WC, Buja LM. Frequency and significance of coronary arterial thrombi and other observations in fatal acute myocardial infarction. A study of 107 necropsy patients. *Am J Med*. 1972;52:425-443.

2. Roberts WC. Coronary arteries in fatal acute myocardial infarction. *Circulation*. 1972;45:215-230. doi:10.1161/01.CIR.45.1.215

3. De Lemos JA, Lindahl B, Mills NL. Type 2 myocardial infarction – poorly understood, under evaluated, and too often ignored. *JAMA Cardiol*. 2024;(9):411-412. doi:10.1001/jamacardio.2024.0127

4. Levin DC, Fallon JT. Significance of the angiographic morphology of localized coronary stenoses: Histopathologic correlations. *Circulation*. 1982;66:316-320. doi:10.1161/01.CIR.66.2.316

5. Davies MJ, Thomas AC. Plaque fissuring--the cause of acute myocardial infarction, sudden ischaemic death, and crescendo angina. *Br Heart J*. 1985;53(4):363-373. doi:10.1136/hrt.53.4.363. PMID:3885978

6. Aversano T, Aversano LT, Passamini E, et al. Thrombolytic therapy vs primary percutaneous coronary intervention for myocardial infarction in patients presenting to hospitals without on-site cardiac surgery: A randomized controlled trial. *JAMA*. 2002;(287):1943-1951. doi:10.1001/jama.287.15.1943

7. Goff DC Jr, Sellers DE, McGovern PG, et al. Knowledge of heart attack symptoms in a population survey in the United States: The REACT Trial. *Arch Intern Med*. 1998;(158):2329-2338. doi:10.1001/archinte.158.21.2329

8. Kudenchuk PJ, Maynard C, Martin JS, et al. Comparison of presentation, treatment, and outcome of acute myocardial infarction in men versus women (The Myocardial Infarction Triage and Intervention Registry). *Am J Cardiol*. 1996;78:9-14. doi:10.1016/S0002-9149(96)00218-4

9. Lee TH, Cook EF, Weisberg M, et al. Acute chest pain in the emergency room: Identification and examination of low-risk patients. *Arch Intern Med*. 1985;145:65-69. doi:10.1001/archinte.1985.00360010085013

10. Rouan GW, Lee TH, Cook EF, et al. Clinical characteristics, and outcome of acute myocardial infarction in patients with initially normal or nonspecific electrocardiograms: A report from the multicenter chest pain study. *Am J Cardiol*. 1989;64:1057-1082. doi:10.1016/0002-9149(89)90857-6

11. Hedges JR, Young GP, Henkel G, et al. Serial ECGs are less accurate than serial CKMB results for ED diagnosis of myocardial infarction. *Ann Emerg Med*. 1992;21:1445-1450. doi:10.1016/S0196-0644(05)80057-5

12. Hedges JR, Rouan G, Toltzis R, et al. Selective determination of creatine kinase levels identifies patients with acute myocardial infarction otherwise unrecognized in the emergency department. *Ann Emerg Med*. 1987;16:248-252. doi:10.1016/S0196-0644(87)80167-1

13. McCarthy BD, Beshansky JR, D'Agostino RB, Selker HP. Missed diagnoses of acute myocardial infarction in the emergency department: Results from a multicenter study. *Ann Emerg Med*. 1993;22:579-582. doi:10.1016/S0196-0644(05)81945-6

14. Lee TH, Rouan GW, Weisberg MC, et al. Sensitivity of routine clinical criteria for diagnosing myocardial infarction within 24 hours of hospitalization. *Ann Intern Med*. 1987;106:181-186. doi:10.7326/0003-4819-106-2-181

15. Hedges JR. Pitfalls in accident and emergency chest pain evaluation. *J Roy Soc Med (London)*. 1995;88:524P-527P.

16. Lee TH, Weisberg MC, Cook F, et al. Evaluation of creatine kinase and creatine kinase-MB for diagnosing myocardial infarction: Clinical impact in the emergency room. *Arch Intern Med*. 1987;147:115-121. doi:10.1001/archinte.1987.00370010113026

17. Rouan GW, Hedges JR, Toltzis R, et al. A chest pain clinic to improve the follow up of patients released from an urban university teaching hospital emergency department. *Ann Emerg Med*. 1987;16:1145-1150. doi:10.1016/S0196-0644(87)80474-2

18. Field DL, Hedges JR, Arnold KJ, et al. Limitations of chest pain follow-up from an urban teaching hospital emergency department. *J Emerg Med*. 1988;6:363-368. doi:10.1016/0736-4679(88)90002-9

19. Hoekstra JW, Hedges JR, Gibler WB, et al. Emergency department CK-MB: A predictor of ischemic complications. *Acad Emerg Med*. 1994;1:17-28. doi:10.1111/j.1553-2712.1994.tb02795.x

20. Hedges JR, Young GP, Henkel GF, et al. Early CK MB elevations predict ischemic events in stable chest pain patients. *Acad Emerg Med*. 1994;1:9-16. doi:10.1111/j.1553-2712.1994.tb02794.x

21. Neumann JT, Twerenbold R, Ojeda F, et al. Application of high-sensitivity troponin in suspected myocardial infarction. *N Engl J Med*. 2019;380:2529-2540. doi:10.1056/NEJMoa1803377

22. Hedges JR. The role of CK MB in chest pain decision making. *J Acc Emerg Med*. 1995;12:101-106. doi:10.1136/emj.12.2.101. PMID:7582402

23. Young GP, Hedges JR, Gibler WB, et al. Do CK MB results affect chest pain decision making in the emergency department? *Ann Emerg Med*. 1991;20:1220-1228.

24. Hedges JR, Gibler WB, Young GP, et al. Multicenter study of creatine kinase- MB use: Effect on chest pain clinical decision making. *Acad Emerg Med*. 1996;3:7-15. doi:10.1111/j.1553-2712.1996.tb03295.x

25. Gibler WB, Young GP, Hedges JR, et al. Acute myocardial infarction in patients with non-diagnostic ECGs: Serial CK MB sampling in the emergency department. *Ann Emerg Med*. 1992;21:504-512. doi:10.1016/S0196-0644(05)82515-6

26. Young GP, Gibler WB, Hedges JR, et al. Serial creatine kinase MB results are a sensitive indicator of acute myocardial infarction in chest pain patients with nondiagnostic electrocardiograms: The Second Emergency Medicine Cardiac Research Group study. *Acad Emerg Med*. 1997;4:869-877. doi:10.1111/j.1553-2712.1997.tb03812.x

27. Gibler WB, Lewis LM, Erb RE, et al. Early detection of acute myocardial infarction in patients presenting with chest pain and nondiagnostic ECGs: Serial CK-MB sampling in the emergency department. *Ann Emerg Med*. 1990;19:1359-1366. doi:10.1016/S0196-0644(05)82598-3

28. Gibler WB, Gibler CD, Weinshenker, et al. Myoglobin as an early indicator of acute myocardial infarction. *Ann Emerg Med*. 1987;16(8):851-856. doi:10.1016/S0196-0644(87)80521-8

29. Bresler MJ, Gibler WB. Acute myocardial infarction: Subtleties of diagnosis in the emergency department. *Ann Emerg Med*. 1990;19(2):2349-2354.

30. Shell WE, DeWood MA, Kligerman M, et al. Early appearance of MB-creatine kinase activity in nontransmural myocardial infarction detected by a sensitive assay for the isoenzyme. *Am J Med*. 1981;71:254-262. doi:10.1016/0002-9343(81)90126-1

31. Hedges JR, Mann NC, Meischke H, et al. Assessment of chest pain onset and out-of-hospital delay using standardized interview questions: The REACT pilot study. *Acad Emerg Med*. 1998;5:773-780. doi:10.1111/j.1553-2712.1998.tb02503.x

32. Bevins NJ, Chae H, Hubbard JA, et al. Emergency department management of chest pain with a high-sensitivity troponin-enabled 0/1-hour rule-out algorithm: Impact on outcomes in a real-world setting. *Am J Clin Pathol*. 2022;157(5):774-780. doi:10.1093/ajcp/aqab192. PMID:34893795

33. Reyes J, Becker BA, D'Angelo J, et al. Utility of serial conventional troponin testing for emergency department patients stratified by HEART score and symptom timing. *Amer J Emerg Med*. 2023;69:173-179. doi:10.1016/j.ajem.2023.04.044

34. Gibler WB, Runyon JP, Levy RC, et al. A rapid diagnostic and treatment center for patients with chest pain in the emergency department. *Ann Emerg Med*. 1995;25:1-8. doi:10.1016/S0196-0644(95)70347-0

35. Gibler WB, Sayre MR, Levy RC, et al. Serial 12-lead electrocardiographic monitoring in patients presenting to the emergency department with chest pain. *J Electrocardiol*. 1994;26:238-243.

36. Gibler WB. Chest pain evaluation in the ED: Beyond triage. *Am J Emerg Med*. 1994;12:121-122. doi:10.1016/0735-6757(94)90219-4

37. Gibler WB. Evaluating patients with chest pain in the ED: Improving speed, efficiency, and cost effectiveness, or teaching an old dog new tricks. *Ann Emerg Med*. 1994;23:381-382. doi:10.1016/S0196-0644(94)90002-7

38. Gibler WB. Evaluating patients with possible acute ischemic coronary syndromes in the emergency department: Evolution of chest pain evaluation and treatment units. *Focus Opinion: Intern Med*. 1994;1(4).

39. National Heart Attack Alert Program, 60 Minutes to Treatment Working Group. Rapid identification and treatment of acute myocardial infarction in the emergency department. *Ann Emerg Med*. 1994;23:311-329. doi:10.1016/S0196-0644(94)70045-1

40. Hoekstra JW, Gibler WB, Levy RC, et al. Emergency department diagnosis of acute myocardial infarction and ischemia: A cost analysis. *Acad Emerg Med*. 1994;1:103-110. doi:10.1111/j.1553-2712.1994.tb02731.x

41. American College of Emergency Physicians, Clinical Policies Subcommittee on Chest Pain. Clinical policy for the initial approach to adults presenting with a chief complaint of chest pain, with no history of trauma. *Ann Emerg Med*. 1995;25:274-299. doi:10.1016/S0196-0644(95)70342-X

42. McCarthy CP, Wasfy JH, Januzzi JL Jr. Is myocardial infarction over diagnosed? *JAMA*. 2024;331(19):1623-1624.

Stimpson JP, Tamirisa K, Keaweʻaimoku Kaholokula J, Ortega AN. Monitoring Public Health During the 2023 Maui Wildfire Using Google Search Trends. *Hawaii J Health Soc Welf*. 2026;85(1):10-16. doi:10.62547/QCKY9141

Monitoring Public Health During the 2023 Maui Wildfire Using Google Search Trends

Jim P. Stimpson, PhD[1], Ketan Tamirisa[2], Joseph Keaweʻaimoku Kaholokula, PhD[3], Alexander N Ortega, PhD[4]

[1] Department of Health Economics, Systems, and Policy, The University of Texas Southwestern Medical Center, [2] Washington University in St. Louis, [3] Department of Native Hawaiian Health, University of Hawaiʻi at Mānoa, [4] Thompson School of Social Work & Public Health, University of Hawaiʻi at Mānoa

Keywords: Wildfires, Natural Disasters, Information Seeking Behavior, Infodemiology, Public Health Surveillance

https://doi.org/10.62547/QCKY9141

Abstract

Wildfires pose acute and long-term threats to public health. This study used Google Trends to assess real-time public interest in health-related topics before, during and after the August 2023 Maui wildfires. Search terms were grouped into four categories: health care access, physical health, mental health, and help-seeking behavior. Daily search interest scores were aggregated and analyzed across three periods: pre-wildfire, wildfire, and post-wildfire. Findings revealed that physical health and health care access search interest remained relatively stable throughout the study period, with no measurable surge during or after the wildfire event. This lack of increase may reflect reliance on pre-established care plans among individuals with chronic respiratory conditions, in-person care-seeking, or prioritization of immediate safety over online information-seeking. In contrast, mental health–related searches rose substantially in the weeks following the wildfire, while help-seeking searches showed episodic fluctuations with notable peaks post-disaster. These findings illustrate how online search patterns can reveal evolving public health priorities in the wake of disasters. Google Trends offers a timely and scalable tool to monitor evolving health concerns during disasters, complementing traditional surveillance systems. Integrating search data into disaster response planning could enhance resource allocation, guide communication strategies, and ensure timely support for emerging needs, particularly mental health recovery following wildfire events.

Introduction

In August 2023, the Hawaiian island of Maui experienced a devastating wildfire that led to loss of life, destruction of homes and businesses, and widespread disruption. Wildfires pose serious public health threats, contributing to direct injuries and exacerbating physical and mental health conditions.[1,2] These events may also influence health-seeking behaviors, prompting individuals to seek information about symptoms, treatment options, or health care access.[3,4] Recent work found significant increases in suicides, overdoses, depressive symptoms, and heightened use of crisis counseling and behavioral health services in the weeks following the Maui wildfires.[4-6] Together, these studies suggest that mental health consequences may be among the most immediate and pronounced health impacts of major wildfires, underscoring the need for timely surveillance and focused interventions.

Moreover, such crises often unfold rapidly, outpacing traditional data collection methods such as hospital records or epidemiological reports, which may lag for weeks or months. Consequently, Google Trends (Google, LLC, Mountain View, CA), which provides publicly available, anonymized data on search query volume, has gained traction as a near real-time tool for monitoring population-level information needs and concerns.[7] These search patterns can reflect immediate community responses, disruptions in care, or calls for help, making Google Trends a powerful information surveillance or "infoveillance" tool.[8-11] The most prominent application, Google Flu Trends, was initially lauded for anticipating seasonal influenza spikes, though it later revealed notable forecasting errors, illustrating the importance of validation and cautious interpretation.[12,13] Search trends have also been used to monitor mental health–related concerns during crises, such as fluctuating searches for anxiety and depression during the COVID-19 pandemic, which were found to correlate with self-reported therapy use and other indicators of treatment need.[14-18] Additionally, emerging studies have demonstrated how Google Trends can reflect public reactions to geohazards like earthquakes and hurricanes, with search activity spiking in affected regions and aligning with media coverage and disaster timelines.[19] Similarly, social media platforms have increasingly been leveraged for disaster surveillance and research. For instance, analyses of Twitter and Facebook data have tracked public concerns, information diffusion, and behavioral responses during crises.[20-24] In another example, a recent analysis of TikTok posts spanning the crisis, immediate aftermath, and long-term recovery phases of the Maui wildfires revealed that the platform played a central role in public information exchange and emotional support.[25] Posts shared during the active wildfire period drew particularly high engagement demonstrating TikTok's importance as a real-time communication channel. These findings underscore how digital tools offer complementary real-time insights into evolving public concerns during disasters, supporting more responsive public health surveillance.

This study used Google Trends search data to examine health-related search interest, including physical and mental health, health care access, and help-seeking before, during, and after the August 2023 wildfires in Hawaiʻi. While previous research has documented increased mental health needs following disasters, including the Maui wildfires, much of this evidence comes from clinical or administrative

data that become available only after substantial delays, limiting their usefulness for rapid response. In contrast, Google Trends provides a near real-time, population-level signal of information-seeking behavior related to physical health, mental health, health care access, and help-seeking. These data can reveal whether changes in public interest and concern are driven by symptom onset, service disruption, or heightened awareness that may not yet be visible in health care utilization statistics. By examining search trends across the disaster timeline, this study aimed to identify emerging health needs, potential barriers to care, and patterns of help-seeking that could inform response strategies and resource allocation in the critical days and weeks after a major wildfire. Such insights can help public health agencies anticipate demand, tailor risk communication, and deploy services more effectively during future disasters.

Methods

Google Trends data were collected for the state of Hawai‘i using the web search option and covered the period from June 1, 2023, to December 31, 2023. The analysis focused on health-related information-seeking behaviors potentially associated with the August 2023 wildfires. Since Google Trends does not provide individual-level data, the population included in this analysis comprises all internet users in Hawai‘i who conducted searches using selected health-related terms during the study period. Google estimates user location primarily through IP address, GPS data for mobile users, and account settings. However, data are typically only available at the state level or for large metropolitan areas. In Hawai‘i the only metropolitan area available for Google Trends data is Honolulu, likely because it meets Google’s minimum search-volume threshold to preserve user anonymity. Maui and other regions do not meet this threshold, preventing access to their localized data. Therefore, Hawai‘i was used as the geographic unit for analysis.

Because Google Trends does not report raw search counts, the exact number of searches underlying each trend is unknown.[26,27] Google Trends suppresses data when search volume is too low, which is a privacy threshold mechanism that maps sparse data to zeros even for regions or terms that were previously stable. These constraints mean that searches cannot be disaggregated to Maui County and that the precise number of users represented is not measurable, which is noted as a limitation in this study.

Search items were organized into 4 thematic categories: health care access (eg, “emergency room,” “hospital near me”), physical health (eg, “asthma,” “burn treatment”), mental health (eg, “anxiety,” “depression”), and help-seeking behavior (eg, “counseling,” “talk to someone”). Search terms shown in **Table 1** were developed through a combination of expert consensus, review of previous infodemiology studies, and preliminary searches in Google Trends to assess term relevance during the wildfire time period. Search term categorization was conducted independently by 2 study authors. Each author reviewed a primary list of search items and assigned them to 1 of the 4 thematic categories based on prior literature and conceptual relevance. Discrepancies and categorization were resolved through discussion with a third author and consensus was reached on final groupings.

Google Trends normalizes search interest on a 0–100 scale, with 100 representing peak popularity during the selected time and region. It does not provide the absolute number of searches. Rather, each value is normalized against all Google search activity in that location and time period, which helps control for population size and overall internet use. However, this normalization depends on the chosen query, time frame, language, and geographic area, which means values are not directly comparable across regions or search terms, as each index is relative to its own search environment.[27]

To capture overall public concern within each category, daily search interest scores were aggregated by summing the individual keyword scores. To reduce day-to-day volatility and facilitate comparison over time, daily aggregated search interest scores were converted to weekly averages. Specifically, the daily summed scores for each category were first totaled across the seven days of each week, then divided by the number of days with data available for that week. To preserve Google Trends’ standardized 0–100 scaling, these weekly sums were further divided by the number of included search terms in the category, ensuring that resulting weekly values reflected the average relative search interest per term while maintaining comparability across weeks and categories.

To examine changes in search interest before, during, and after the 2023 Maui wildfires, 3 temporal phases were defined: pre-wildfire (calendar year weeks 27–31), wildfire (weeks 32–33), and post-wildfire (weeks 34–39). The wildfire period was defined using the official timeline of the 2023 Maui wildfires, which identifies August 8–19, 2023 (calendar weeks 32–33), as the main emergency period when active burning, evacuations, and immediate health impacts were most acute.[28] Although some fires were not fully contained until September 28, this analysis focused on the concentrated emergency period to minimize potential confounding effects of unrelated events before and after the disaster.

A line graph was generated using Microsoft Excel for Mac Version 16.1(Microsoft Corporation, Redmond, WA) to visualize temporal trends and identify potential spikes in search interest corresponding to key dates during the wildfire event. Descriptive statistics, including means and standard deviations, were calculated for each category by disaster period. In addition, one-way analysis of variance (ANOVA) was used to compare mean weekly search interest across the three phases for each category. Effect sizes were calculated using eta-squared (η^2) to assess the proportion of variance explained by phase. Values of .01,.06, and.14 for η^2 were considered as benchmarks for small, medium, and large effects, respectively.[29,30] As a sensitivity analysis, the analysis was repeated using a broader time window (weeks 22–52) with the same wildfire definition (weeks 32–33), which increased the number of pre- and post-wildfire observations but introduced greater temporal imbalance. Sta-

Table 1. Components of Health-Related Google Search Term Categories: State of Hawai'i, June 1, 2023, to December 31, 2023

Health Care Access	Physical Health	Mental and Cognitive Health	Help-Seeking Behavior
emergency room	asthma	anxiety	counseling
urgent care	smoke	can't sleep	mental health hotline
hospital near me	difficulty breathing	depression	talk to someone
	inhaler	difficulty concentrating	
	burn	dizziness	
	burn treatment	headache	
	urgent care for burns	insomnia	
		mental fatigue	
		mental health	
		migraine	
		nausea	
		panic attacks	
		post-traumatic stress	
		PTSD	
		sadness	
		stress	

tistical analyses were conducted using Stata 19.5 software (StataCorp LLC, College Station, TX).

Results

Figure 1 displays weekly average Google Trends scores from week 22 to week 52 of 2023 for 4 search categories: health care access, physical health, mental health, and help-seeking behavior. The Hawai'i wildfire period (weeks 32–33) is marked by vertical dashed lines. Health care access searches consistently had the highest interest, ranging from 12 to 32, with a notable peak in week 52. Physical health searches remained minimal throughout ranging from 0 to 5. Mental health searches showed moderate variation across the study period, ranging from 5–12, with peaks post-wildfire observed in weeks 35, 41, and 44. Help-seeking behavior searches ranged from 0 to 17, with peaks post-wildfire observed in weeks 36, 40, and 43.

As shown in **Table 2**, mental health search interest showed a statistically significant difference across phases (P = .02), with a very large effect size (η^2 = .56). Mean search interest for mental health declined during the wildfire phase (mean = 5.67) compared with both the pre-wildfire (mean = 8.56) and post-wildfire periods (mean = 9.11). Health care access showed a large effect size (η^2 = .27) but did not reach statistical significance (P = .24). Physical health showed a small effect size (η^2 = .09) and was not statistically significant (P = .56). Help-seeking behavior showed a medium effect size (η^2 = .05) and was not statistically significant (P = .78).

Discussion

Google Trends data from the August 2023 Maui wildfires reveal distinct temporal shifts in internet searches, with stable interest in physical health and health care access topics, episodic peaks in help-seeking, and a significant increase in mental health–related searches in the weeks following the disaster. Contrary to expectations, searches related to physical health symptoms did not spike during or immediately after the wildfire period despite well-documented smoke exposure in Maui.[31] This absence of a visible surge in online interest does not necessarily indicate a lack of symptoms; rather, individuals with chronic respiratory conditions such as asthma or COPD may have relied on pre-established action plans or sought care directly through urgent care centers, clinicians, or emergency departments, reducing the need for online searches. Health care access searches also showed no significant increases and dipped only slightly during the wildfire period. Together, these patterns suggest that physical health concerns, including respiratory issues and potential disruptions in care, may not have driven substantial online search activity during the acute phase of the disaster, possibly because people relied on existing care pathways or prioritized immediate safety over information-seeking.

In contrast, mental health–related searches were consistently among the highest categories and showed marked increases in the weeks following the wildfire. This pattern is consistent with prior research showing that psychological distress often intensifies after traumatic events, underscoring the need for sustained access to mental health services well into the recovery phase.[32-34] This observed trend may suggest potential barriers to in-person services or limited public awareness of available resources.[4]

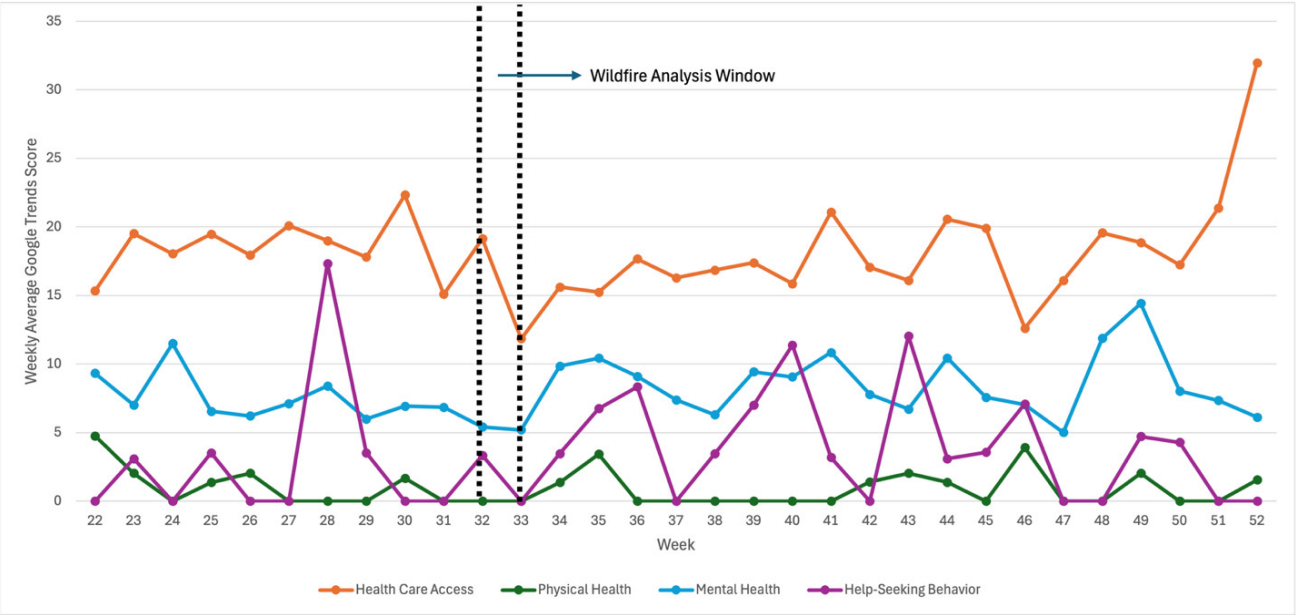

Figure 1. Weekly Average Google Search Trend Score by Health-Related Category in the State of Hawai'i from June 1, 2023 (week 22) to December 31, 2023 (week 52)

Table 2. Mean and Standard Deviation (SD) of Daily Google Search Interest by Health-Related Category and Time Period, State of Hawai'i, July 2, 2023 – September 30, 2023, with Results of One-Way ANOVA and Effect Sizes

Category[a]	Pre-Wildfire[b], mean (SD)	Wildfire, mean (SD)	Post-Wildfire, mean (SD)	One-Way ANOVA *P-value*	Eta-squared η^2 (effect size)[c]
Health Care Access	17.56 (2.56)	16.63 (3.35)	18.57 (3.50)	.24	.27
Physical Health	1.33 (1.65)	1.88 (2.10)	1.00 (1.15)	.56	.09
Mental Health	8.56 (1.07)	5.67 (1.15)	9.11 (1.05)	.02	.56
Help-Seeking Behavior	3.89 (4.91)	3.50 (1.00)	2.78 (2.17)	.78	.05

Notes:
[a]Health-related categories are based on aggregated daily Google search interest scores (0–100 scale) within each category: health care access, physical health, mental health, and help-seeking behavior.
[b]Time periods are defined as: pre-wildfire = weeks 27–31 (July 2 – August 5, 2023); wildfire = weeks 32–33 (August 6 – August 19, 2023); post-wildfire = weeks 34–39 (August 20 – September 30, 2023).
[c]η^2 (eta-squared) is reported as a measure of effect size, interpreted as: small (.01), medium (.06), large (.14) following Cohen's guidelines.

Several prior studies have explored the utility of Google Trends for public health surveillance across diverse illnesses, including influenza, COVID-19, environmental exposures, and mental health.[8-12,14-17] This study adds to a growing body of work demonstrating the value and limitations of Google Trends for public health surveillance.[26,27] Since the discontinuation of Google Flu Trends, methodological refinements have improved the use of search data when triangulated with traditional epidemiologic indicators.[13,18] While these prior studies have shown that search behavior can capture acute concerns such as evacuation and mental health needs, relatively less is known about how these behaviors evolve across the full disaster timeline or how they can complement existing data sources. This study illustrates how thematic analysis of search queries can illuminate shifting public priorities during and after a wildfire, providing a window into emerging health needs and communication gaps. By highlighting these dynamics, the findings demonstrate the potential for internet search data to strengthen disaster preparedness and facilitate more responsive public health communication.

Limitations

This study has several limitations. First, Google Trends provides only relative, not absolute-search interest, and does not capture clinical outcomes or care seeking behaviors. Aggregating keyword scores allowed the team to assess broader topic-level attention; however, this method introduces interpretive limitations. Second, this study used Google Trends data from the state of Hawai'i because more granular data at the county or city level were not available. Consequently, the results are disproportionately weighted toward O'ahu, the island on which the majority of Hawai'i's

residents live, limiting the generalizability of findings for the Maui population. Third, online search behavior may not represent all populations, particularly those with limited internet access or digital literacy challenges, or strong reliance on in-person care may be underrepresented in this data set. Fourth, although the authors observed heightened mental-health-related search activity in the post-wildfire period, the retrospective design of the study precludes any claim that these observations influenced resource allocation. The analysis was conducted after the event and thus could not inform real-time decision-making. Future investigations designed for prospective monitoring, integrating real-time search analytics with health-system planning, would be needed to evaluate whether Google Trends can serve as an actionable tool for allocating resources during crises. Finally, the increase in mental-health searches likely reflects a broader shift toward emotional recovery after trauma, whereas physical-health concerns among individuals with chronic pulmonary conditions may have been addressed through established care pathways that did not generate additional online queries.

Conclusion

Overall, findings indicate that the wildfire was accompanied by heightened online attention to mental health, underscoring the unique role of disasters in shaping public information needs beyond physical health concerns. This pattern may reflect the acute, immediate nature of physical health and access needs that are often addressed offline through established care plans or emergency services. In contrast, mental health needs may emerge more gradually and be shaped by stigma, leading individuals to seek information online.[35-37] These findings highlight the potential value of Google Trends as a complementary tool for real-time public health surveillance. While the data alone are insufficient to guide immediate disaster response, search trends can provide early signals of shifting public concerns, particularly in the post-disaster phase, especially when integrated with clinical data, environmental indicators, and social media data. As digital surveillance methods continue to evolve, incorporating such behavior into multi-source monitoring systems may enhance situational awareness and guide more responsive, data-informed public health initiatives during and after natural disasters, such as wildfires.

Conflict of Interest and Disclosures

None of the authors identify any conflicts of interest. Research reported in this publication was supported by the National Institute on Minority Health and Health Disparities of the National Institutes of Health under Award Number R61MD019939. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Submitted: April 21, 2025 PST. Accepted: November 09, 2025 PST. Published: January 02, 2026 PST.

References

1. Reid CE, Brauer M, Johnston FH, Jerrett M, Balmes JR, Elliott CT. Critical review of health impacts of wildfire smoke exposure. *Environ Health Perspect*. 2016;124(9):1334-1343. doi:10.1289/ehp.1409277

2. Black C, Tesfaigzi Y, Bassein JA, Miller LA. Wildfire smoke exposure and human health: significant gaps in research for a growing public health issue. *Environ Toxicol Pharmacol*. 2017;55:186-195. doi:10.1016/j.etap.2017.08.022

3. Goldmann E, Galea S. Mental health consequences of disasters. *Annu Rev Public Health*. 2014;35:169-183. doi:10.1146/annurev-publhealth-032013-182435

4. Rivera-González AC, Purtle J, Kaholokula JK, Stimpson JP, Ortega AN. Maui wildfire and 988 suicide and crisis lifeline call volume and capacity. *JAMA Netw Open*. 2024;7(11):e2446523. doi:10.1001/jamanetworkopen.2024.46523

5. Purtle J, Machavariani E, Rivera-González AC, et al. Increases in Suicides and Overdoses During the 2023 Wildfires in Maui, Hawai'i. *JAMA*. Published online August 6, 2025:e2511146. doi:10.1001/jama.2025.11146

6. Juarez R, Phankitnirundorn K, Ozorio Dutra SV, Bond-Smith D, Lee AG, Maunakea AK. Health and social support in the aftermath of the Maui wildfires. *JAMA Netw Open*. 2025;8(8):e2525430. doi:10.1001/jamanetworkopen.2025.25430

7. Mavragani A, Ochoa G. Google Trends in infodemiology and infoveillance: methodology framework. *JMIR Public Health Surveill*. 2019;5(2):e13439. doi:10.2196/13439

8. Nuti SV, Wayda B, Ranasinghe I, et al. The use of Google Trends in health care research: a systematic review. *PloS One*. 2014;9(10):e109583. doi:10.1371/journal.pone.0109583

9. Qiu A, Meadows K, Ye F, Iyawe O, Kenneth-Nwosa K. Quantifying patient demand for orthopedics care by region through Google Trends analysis: descriptive epidemiology study. *Online J Public Health Inform*. 2025;17:e63560. doi:10.2196/63560

10. Nguyen D, Javaheri J, Sanchez R, Han V. Popular treatments of psoriasis on social media: Google Trends analysis. *JMIR Dermatol*. 2025;8:e70067. doi:10.2196/70067

11. Matei SA, Kulzick R, Sinclair-Chapman V, Potts L. Setting the agenda in environmental crisis: relationships between tweets, Google search trends, and newspaper coverage during the California drought. *PLOS ONE*. 2021;16(12):e0259494. doi:10.1371/journal.pone.0259494

12. Pervaiz F, Pervaiz M, Abdur Rehman N, Saif U. FluBreaks: early epidemic detection from Google Flu Trends. *J Med Internet Res*. 2012;14(5):e125. doi:10.2196/jmir.2102

13. Yang S, Santillana M, Kou SC. Accurate estimation of influenza epidemics using Google search data via ARGO. *Proc Natl Acad Sci U S A*. 2015;112(47):14473-14478. doi:10.1073/pnas.1515373112

14. Wang A, McCarron R, Azzam D, Stehli A, Xiong G, DeMartini J. Utilizing big data from Google Trends to map population depression in the United States: exploratory infodemiology study. *JMIR Ment Health*. 2022;9(3):e35253. doi:10.2196/35253

15. Hoerger M, Alonzi S, Perry LM, Voss HM, Easwar S, Gerhart JI. Impact of the COVID-19 pandemic on mental health: real-time surveillance using Google Trends. *Psychol Trauma*. 2020;12(6):567-568. doi:10.1037/tra0000872

16. Vaidyanathan U, Sun Y, Shekel T, et al. An evaluation of internet searches as a marker of trends in population mental health in the US. *Sci Rep*. 2022;12(1):8946. doi:10.1038/s41598-022-12952-5

17. Sycińska-Dziarnowska M, Szyszka-Sommerfeld L, Kłoda K, Simeone M, Woźniak K, Spagnuolo G. Mental health interest and its prediction during the COVID-19 pandemic using Google Trends. *Int J Environ Res Public Health*. 2021;18(23):12369. doi:10.3390/ijerph182312369

18. Rovetta A. Reliability of Google Trends: Analysis of the limits and potential of web infoveillance during COVID-19 pandemic and for future research. *Front Res Metr Anal*. 2021;6:670226. doi:10.3389/frma.2021.670226

19. Erokhin D, Komendantova N. Analyzing public interest in geohazards using Google Trends data. *Geosciences*. 2024;14(10):266. doi:10.3390/geosciences14100266

20. Ford B, Burke M, Lassman W, Pfister G, Pierce JR. Status update: is smoke on your mind? Using social media to assess smoke exposure. *Atmos Chem Phys*. 2017;17(12):7541-7554. doi:10.5194/acp-17-7541-2017

21. García YE, Villa-Pérez ME, Li K, et al. Wildfires and social media discourse: exploring mental health and emotional wellbeing through Twitter. *Front Public Health*. 2024;12:1349609. doi:10.3389/fpubh.2024.1349609

22. Ogie R, Moore A, Wickramasuriya R, Amirghasemi M, James S, Dilworth T. Twitter data from the 2019–20 Australian bushfires reveals participatory and temporal variations in social media use for disaster recovery. *Sci Rep*. 2022;12(1):16914. doi:10.1038/s41598-022-21265-6

23. Postma JM, Marko T, Meyer M, et al. Assessing community response to wildfire smoke: a multimethod study using social media. *Public Health Nurs*. 2023;40(1):153-162. doi:10.1111/phn.13140

24. Unal Colak F, Yılmaz S. Social media use during August 2021 forest fire disaster in Turkey. *Disaster Med Public Health Prep*. 2021;15(6):679-681. doi:10.1017/dmp.2021.363

25. Stimpson JP, Srivastava A, Tamirisa K, Kaholokula JK, Ortega AN. Crisis communication about the Maui wildfires on TikTok: content analysis of engagement with Maui wildfire–related posts over 1 year. *JMIR Form Res*. 2025;9:e67515-e67515. doi:10.2196/67515

26. Neumann K, Mason SM, Farkas K, Santaularia NJ, Ahern J, Riddell CA. Harnessing Google Health Trends data for epidemiologic research. *Am J Epidemiol*. 2023;192(3):430-437. doi:10.1093/aje/kwac171

27. Cebrián E, Domenech J. Is Google Trends a quality data source? *Appl Econ Lett*. 2023;30(6):811-815. doi:10.1080/13504851.2021.2023088

28. Fire Safety Research Institute, Kerber S, Alkonis D. *Lahaina Fire Comprehensive Timeline Report*. UL Research Institutes; 2024. doi:10.54206/102376/VQKQ5427

29. Sullivan GM, Feinn R. Using effect size-or why the P value is not enough. *J Grad Med Educ*. 2012;4(3):279-282. doi:10.4300/JGME-D-12-00156.1

30. Richardson JTE. Eta squared and partial eta squared as measures of effect size in educational research. *Educ Res Rev*. 2011;6(2):135-147. doi:10.1016/j.edurev.2010.12.001

31. Mass C, Ovens D. The meteorology of the August 2023 Maui wildfire. *Weather Forecast*. 2024;39(8):1097-1115. doi:10.1175/WAF-D-23-0210.1

32. Galea S, Nandi A, Vlahov D. The epidemiology of post-traumatic stress disorder after disasters. *Epidemiol Rev*. 2005;27:78-91. doi:10.1093/epirev/mxi003

33. Norris FH, Friedman MJ, Watson PJ. 60,000 disaster victims speak: part II. summary and implications of the disaster mental health research. *Psychiatry*. 2002;65(3):240-260. doi:10.1521/psyc.65.3.240.20169

34. Purtle J, Rivera-González AC, Mercado DL, et al. Growing inequities in mental health crisis services offered to indigent patients in Puerto Rico versus the US states before and after Hurricanes Maria and Irma. *Health Serv Res*. 2023;58(2):325-331. doi:10.1111/1475-6773.14092

35. Berger M, Wagner TH, Baker LC. Internet use and stigmatized illness. *Soc Sci Med 1982*. 2005;61(8):1821-1827. doi:10.1016/j.socscimed.2005.03.025

36. Mason NF, Francis DB. Information-seeking and use of primary care mental health services among Gulf Coast survivors of natural disasters. *Disaster Med Public Health Prep*. 2021;15(6):735-740. doi:10.1017/dmp.2020.99

37. Chan FHF, Lin X, Griva K, Subramaniam M, Ćelić I, Tudor Car L. Information needs and sources of information among people with depression and anxiety: a scoping review. *BMC Psychiatry*. 2022;22(1):502. doi:10.1186/s12888-022-04146-0

Cape M. Bioinformatics Research at University of Hawai'i : an Overview and Undergraduate Student Perspective. *Hawaii J Health Soc Welf*. 2026;85(1):17-20. doi:10.62547/PVZI7945

Bioinformatics Research at University of Hawai'i: an Overview and Undergraduate Student Perspective

Micaiah Cape[1]

[1] Information and Computer Sciences Department, University of Hawai'i at Mānoa

Keywords: Bioinfomatics, university of Hawaii, undergraduate research, bioinformatics education

https://doi.org/10.62547/PVZI7945

The Medical School Hotline of the University of Hawai'i John A. Burns School of Medicine was founded in 1993, by Satoru Izutsu PhD (former vice-dean UH JABSOM). It is a monthly column and is edited by Kathleen Kihmm Connolly PhD; HJH&SW Contributing Editor.

Introduction

Bioinformatics uses computers, databases, math, and statistics to analyze large amounts of biological information. It is a rapidly expanding field due to the availability and growing quantity of biological data. For example, the GenBank, a public database, contains all known DNA sequences: trillions of base pairs from billions of nucleotide sequences.[1] Additionally, the cost of sequencing a human genome has also fallen dramatically, from $1 million in 2007 to less than $1000 in 2023,[2] which allows much more data to be produced and analyzed.

As a result, applying bioinformatics methods to investigate the molecular mechanisms of diseases is a burgeoning field of research. For example, bioinformatics can be used to identify specific genetic biomarkers, generate mutation data, determine microbiota composition (if applicable), or identify cellular pathways implicated in specific types of cancers. These can, in turn, be used to create diagnostic or prognostic models, which can be translated to provide better screening or better management of cancer symptoms. Nearly 150 000 cancer bioinformatics-related articles have been published and are available on PubMed in 2025, with more than 15 000 published in 2024 alone.

Despite the importance of bioinformatics, education at the undergraduate level remains relatively limited nationally, with most universities exclusively offering graduate degrees. Significant barriers in implementing bioinformatics undergraduate education have also been reported in the literature, with the most common being lack of faculty training, lack of undergraduate interest, or insufficient mathematics background from undergraduate students.[3] Within the University of Hawai'i (UH) System, one of the only consistently offered undergraduate-level bioinformatics course is Biology 483,[4] which is an introduction to bioinformatics offered at the Mānoa campus. Information and Computer Sciences courses 475 and 476 focus on the algorithmic components of bioinformatics[5,6]; however, these classes were last offered in 2013. UH also does not offer an undergraduate bioinformatics degree.

Bioinformatics at the John A. Burns School of Medicine (JABSOM)

Despite challenges in bioinformatics education at the undergraduate level, undergraduates can get exposure to bioinformatics through mentored research. JABSOM has a few opportunities for undergraduates looking for research in bioinformatics. For example, the Bioinformatics Core Facility, led by Dr. Youping Deng, is looking to develop precision medicine for cancer using both bioinformatics and experimental approaches.[7] Ongoing projects focus on cancer disparities affecting Native Hawaiian/Pacific Islanders (NHPI) in Hawai'i, such as investigating gut microbiome and function in NHPI colorectal cancer patients, or identifying genetic function in NHPI with triple-negative breast cancer.[8] Other projects include creating a diagnostic model for non-small cell lung cancer[9] and identification of protein biomarkers for pancreatic cancer.[10] These types of research can pave the way for clinical trials, better screening, earlier detection, and better symptom management of these cancers. Undergraduates may experience such research through many programs offered at the University of Hawai'i at Mānoa (UHM), such as the Maximizing Access to Research Careers (MARC)[11] and Minority Health Research Training (MHRT)[12] programs. In addition, Dr. Deng recently taught a graduate level bioinformatics course that focused on bioinformatics approaches for functional genomics[13] that is open to students outside the department and has no prerequisites.

JABSOM also runs the IDeA Networks for Biomedical Research Excellence (INBRE) program,[14] which is designed to expose undergraduates to mentored biomedical research. Undergraduates choose a mentor from one of INBRE's partnering institutions (including those from JABSOM's Bioinformatics Core Facility) to participate in a research project over the fall semester and present their findings at the INBRE undergraduate symposium in the following spring. In the most recent symposium in 2025, a handful of posters had topics on cancer bioinformatics, mentored by both JABSOM and UH Cancer Center faculty. INBRE is open to any undergraduate major in the biomedical sciences, who has a GPA above 2.75 and has completed 1 semester at university. This makes it an ideal program for undergraduates looking for early research experience. In addition, students may elect to participate in INBRE over consecutive semesters, which makes it possible for longer, more complicated projects in bioinformatics.

Over the summer, INBRE also offers a free, no-credit, 8-week course in bioinformatics. Students get access to

Table 1. List of Bioinformatics Opportunities for Undergraduates at University of Hawai'i at Mānoa (UHM)

Bioinformatics opportunity/ course	Description	Prerequisites
Course: BIOL/MBBE 483 (Bioinformatics)	3-credit course – Teaches the computational tools necessary to analyze large amounts of biological data.	• BIOL 171 (1 semester of General Biology)
Course: QHS 610/611	Both 3-credit courses – the course sequence focuses on hands-on bioinformatics training with an emphasis on human disease.	• None for QHS 610, • QHS 610 is a prerequisite for QHS 611
Research: U54 summer genomics	A hands-on program to train the next generation of genomic scientists.	N/A
Research: IDeA Networks of Biomedical Research Excellence (INBRE)	Promotes undergraduate research and education in biomedical sciences at the University of Hawai'i and partner institutions.	• 1 semester of undergraduate at UHM or partnering institutions • 2.75 GPA • Biomedical sciences major
Course: INBRE Bioinformatics Course	A no-credit course that provides technical training for undergraduates in bioinformatics, using the R programming language.	• Recommended to be an INBRE student
Research: Minority Health Research Training (MHRT)	Provides research training for undergraduates in tropical medicine, infectious diseases, and social and behavioral health sciences.	• 2 years of undergraduate, any major • Underrepresented backgrounds encouraged
Research: Maximizing Access to Research Careers (MARC)	Trains underrepresented students at UHM in biological research.	• Full-time student at UHM • Science, technology, engineering or mathematics (STEM) major • 2-3 years of undergrad left • Underrepresented backgrounds encouraged

web-based DataCamp modules that go over the R programming language by combining video tutorials and hands-on, interactive programming. Basic skills for bioinformatics research such as statistics and data visualization are taught. The course is supplemented by guest speakers from the bioinformatics core at JABSOM, offering undergraduates valuable insight into bioinformatics research.

INBRE also links students with other bioinformatics research opportunities. The U54 genomics training program was advertised at the 2024 INBRE undergraduate symposium, and INBRE students with a background in bioinformatics were encouraged to apply. U54 is an intensive summer program that trains next generation of genomic. At U54, every undergraduate is paired with a faculty mentor from JABSOM or UH Cancer Center to conduct cancer research, which can include bioinformatics. Undergraduates also shadow genomics professionals in a wet lab setting, which gives them an insight into how and where the data they are analyzing in their bioinformatics projects come from. The 2024 cohort had 2 undergraduates, but has expanded to 4 undergraduates (with the 2 original undergraduates continuing) in 2025. See **Table 1** for list of bioinformatics opportunities for undergraduates at UHM.

Personal Experience in Bioinformatics as an Undergraduate at JABSOM

As an undergraduate student, I personally have participated in both INBRE and U54 programs. Bioinformatics was the perfect fit for me as I am a computer science major, and I am interested in how computers can be applied towards medical research. The U54 program initially paired me with Dr. Yuanyuan Fu from JABSOM's bioinformatics core, and I continued working with her through the fall and spring semesters as part of INBRE. I was assigned to her project of investigating disparities in Native Hawaiian colorectal cancer patients. Native Hawaiians have higher mortality rates and earlier onset of colorectal cancer compared to other populations, so our aim was to use bioinformatics to analyze their genomic/microbiome data to explain these disparities. Both programs, combined with Dr. Fu's mentorship, provided hands-on experience in bioinformatics research and development of specific research skills.

At the start of the mentorship, I was unfamiliar with bioinformatics; thus it was suggested to break the project down to bite-size pieces to complete every week. For example, I learned how to filter data on week 1, and the next week I learned a bioinformatics tool to analyze the filtered data. The INBRE bioinformatics course was also very helpful during these beginning stages, as I drew parallels be-

tween the course content and the research project. When errors occurred, Dr. Fu would spend time helping me to debug or send me similar code she wrote, which was very helpful and allowed me to avoid similar errors in the future.

This type of mentorship allowed the project to be digestible while also taking a full-time course load at UHM. This excited me to learn the "next" step that was coming up the following week. After more than a year of being mentored, I went from having no knowledge about bioinformatics to being able to utilize common bioinformatics tools to analyze genomics and metagenomics data. I have also started to appreciate the practical application of computer science to bioinformatics research. Participation in both INBRE and U54 programs motivated me to keep learning about bioinformatics, and evolved into Dr. Fu serving as the mentor for my undergraduate senior honors project. I will continue working with her on the bioinformatics project on colorectal cancer.

Conclusion

JABSOM has a strong Bioinformatics Core Facility that investigates and conducts research on many types of cancers, including those that disproportionately affect NHPI. Participating in research at JABSOM is a way undergraduates can learn bioinformatics. While there is no formal undergraduate bioinformatics major offered at UH, JABSOM-affiliated programs—such as INBRE and U54—show that through mentored research and accessible training, undergraduates can thrive in this field and contribute meaningfully to bioinformatics research.

As the availability and quantity of biological data continue to increase, opportunities will also increase for bioinformatics researchers who can analyze the data to increase medical knowledge and ultimately improve health outcomes. To promote undergraduate interest in bioinformatics, advertising research opportunities to other undergraduate departments at UHM, such as computer science and mathematics, may be a first step. The future of bioinformatics at JABSOM is promising, and getting more students engaged in this field is a good way to train the next generation of bioinformatics researchers to serve the state of Hawai'i.

Submitted: September 18, 2025 PST. Accepted: December 07, 2025 PST. Published: January 05, 2026 PST.

References

1. GenBank and WGS Statistics. Accessed August 27, 2025. https://www.ncbi.nlm.nih.gov/genbank/statistics/

2. Whole Genome Sequencing cost 2023. Accessed August 25, 2025. https://3billion.io/blog/whole-genome-sequencing-cost-2023

3. Williams JJ, Drew JC, Galindo-Gonzalez S, Robic S, Dinsdale E, et al. Barriers to integration of bioinformatics into undergraduate life sciences education: A national study of US life sciences faculty uncover significant barriers to integrating bioinformatics into undergraduate instruction. *PLOS ONE*. 2019;14(11):e0224288. doi:10.1371/journal.pone.0224288

4. BIOL 483 - Introduction to Bioinformatics Topics for Biologists. 2025-2026 UH Mānoa Catalog. Accessed September 16, 2025. https://catalog.manoa.hawaii.edu/preview_course_nopop.php?catoid=2&coid=35343

5. ICS 475 - Introduction to Bioinformatics Sequences and Genomes Analysis. 2025-2026 UH Mānoa Catalog. Accessed September 16, 2025. https://catalog.manoa.hawaii.edu/preview_course_nopop.php?catoid=2&coid=38199

6. ICS 476 - Bioinformatics Algorithms and Tool Development. 2025-2026 UH Mānoa Catalog. Accessed September 16, 2025. https://catalog.manoa.hawaii.edu/preview_course_nopop.php?catoid=2&coid=38200

7. Deng, Youping PhD. Accessed August 27, 2025. https://www.uhcancercenter.org/deng-youping

8. Nguyen ET, Cheng SH, Chang CS, et al. Gene expression profiling of the tumor microenvironment in Asian American and Native Hawaiian/Pacific Islander women with triple negative breast cancer. *J Clin Oncol*. 2025;43(16_suppl):e12622-e12622. doi:10.1200/JCO.2025.43.16_suppl.e12622

9. Gao Z, Nasu M, Devendra G, et al. A robust machine learning model based on ribosomal-subunit-derived piRNAs for diagnostic potential of nonsmall cell lung cancer across multicentre, large-scale of sequencing data. *Clin Transl Med*. 2025;15(8):e70418. doi:10.1002/ctm2.70418

10. Zhu J, Wu K, Liu S, et al. Proteome-wide association study and functional validation identify novel protein markers for pancreatic ductal adenocarcinoma. *GigaScience*. 2024;13:giae012. doi:10.1093/gigascience/giae012

11. Maximizing Access to Research Careers at the University of Hawaii Manoa (MARC-UHM) | Maximizing Access to Research Careers at the University of Hawaii Manoa. January 6, 2024. Accessed September 16, 2025. https://marc-uhm.jabsom.hawaii.edu/

12. MHRT Program: Transdisciplinary Health Disparities Research Training Information | DEPARTMENT OF TROPICAL MEDICINE, MEDICAL MICROBIOLOGY & PHARMACOLOGY. Accessed September 16, 2025. https://manoa.hawaii.edu/tropicalmedicine/?page_id=1467

13. QHS 611 Bioinformatics II • Section 001. Accessed August 26, 2025. https://www.sis.hawaii.edu/uhdad/avail.class?i=MAN&t=202530&c=89100

14. INBRE V -- Opportunities for Aspiring Biomedical Researchers. September 1, 2025. Accessed August 27, 2025. https://inbre.jabsom.hawaii.edu/

Hawai'i Journal of Health & Social Welfare
General Recommendations on Data Presentation and Statistical Reporting (Biostatistical Guideline for HJH&SW)
[Adapted from Annals of Internal Medicine & American Journal of Public Health]

The following guidelines are developed based on many common errors we see in manuscripts submitted to HJH&SW. They are not meant to be all encompassing, or be restrictive to authors who feel that their data must be presented differently for legitimate reasons. We hope they are helpful to you; in turn, following these guidelines will reduce or eliminate the common errors we address with authors later in the publication process.

Percentages: Report percentages to one decimal place (eg, 26.7%) when sample size is >=200. For smaller samples (<200), do not use decimal places (eg, 27%, not 26.7%), to avoid the appearance of a level of precision that is not present.

Standard deviations (SD)/standard errors (SE): Please specify the measures used: using "mean (SD)" for data summary and description; to show sampling variability, consider reporting confidence intervals, rather than standard errors, when possible, to avoid confusion.

Population parameters versus sample statistics: Using Greek letters to represent population parameters and Roman letters to represent estimates of those parameters in tables and text. For ex ample, when reporting regression analysis results, Greek symbol (ß), or Beta (b) should only be used in the text when describing the equations or parameters being estimated, never in reference to the results based on sample data. Instead, one can use "b" or ß for unstandardized regression parameter estimates, and "B" or ß for standardized regression parameter estimates.

***P* values:** Using *P* values to present statistical significance, the actual observed *P* value should be presented. For *P* values between .001 and .20, please report the value to the nearest thousandth (eg, *P*=.123). For *P* values greater than .20, please report the value to the nearest hundredth (eg, *P* =.34). If the observed *P* value is great than *.999*, it should be expressed as "*P* > *.99*". For a *P* value less than .001, report as "*P*<.001". Under no circumstance should the symbol "NS" or "ns" (for not significant) be used in place of actual *P* values.

"Trend": Use the word trend when describing a test for trend or dose-response. Avoid using it to refer to *P* values near but not below .05. In such instances, simply report a difference and the confidence interval of the difference (if appropriate), with or without the *P* value.

One-sided tests: There are very rare circumstances where a "one sided" significance test is appropriate, eg, non-inferiority trials. Therefore, "two-sided" significance tests are the rule, not the ex ception. Do not report one-sided significance test unless it can be justified and presented in the experimental design section.

Statistical software: Specify in the statistical analysis section the statistical software used for analysis (version, manufacturer, and manufacturer's location), eg, SAS software, version 9.2 (SAS Institute Inc., Cary, NC).

Comparisons of interventions: Focus on between-group differ ences, with 95% confidence intervals of the differences, and not on within-group differences.

***Post-hoc* pairwise comparisons**: It is important to first test the overall hypothesis. One should conduct *post-hoc* analysis if and only if the overall hypothesis is rejected.

Clinically meaningful estimates: Report results using meaningful metrics rather than reporting raw results. For example, instead of the log odds ratio from a logistic regression, authors should transform coefficients into the appropriate measure of effect size, eg, odds ratio. Avoid using an estimate, such as an odds ratio or relative risk, for a one unit change in the factor of interest when a 1-unit change lacks clinical meaning (age, mm Hg of blood pressure, or any other continuous or interval measurement with small units). Instead, reporting effort for a clinically meaningful change (eg, for every 10 years of increase of age, for an increase of one standard deviation (or interquartile range) of blood pressure), along with 95% confidence intervals.

Risk ratios: Describe the risk ratio accurately. For instance, an odds ratio of 3.94 indicates that the outcome is almost 4 times as likely to occur, compared with the reference group, and indicates a nearly 3-fold increase in risk, not a nearly 4-fold increase in risk.

Longitudinal data: Consider appropriate longitudinal data analyses if the outcome variables were measured at multiple time points, such as mixed-effects models or generalized estimating equation approaches, which can address the within-subject variability.

Sample size, response rate, attrition rate: Please clearly indicate in the methods section: the total number of participants, the time period of the study, response rate (if any), and attrition rate (if any).

Tables (general): Avoid the presentation of raw parameter estimates, if such parameters have no clear interpretation. For instance, the results from Cox proportional hazard models should be presented as the exponentiated parameter estimates, (ie, the hazard ratios) and their corresponding 95% confidence intervals, rather than the raw estimates. The inclusion of *P*-values in tables is unnecessary in the presence of 95% confidence intervals.

Descriptive tables: In tables that simply describe characteristics of 2 or more groups (eg, Table 1 of a clinical trial), report averages with standard deviations, not standard errors, when data are nor mally distributed. Report median (minimum, maximum) or median (25th, 75th percentile [interquartile range, or IQR]) when data are not normally distributed.

Figures (general): Avoid using pie charts; avoid using simple bar plots or histograms without measures of variability; provide raw data (numerators and denominators) in the margins of meta-analysis forest plots; provide numbers of subjects at risk at different times in survival plots.

Missing values: Always report the frequency of missing variables and how missing data was handled in the analysis. Consider add ing a column to tables or a footnote that makes clear the amount of missing data.

Removal of data points: Unless fully justifiable, all subjects included in the study should be analyzed. Any exclusion of values or subjects should be reported and justified. When influential observations exist, it is suggested that the data is analyzed both with and without such influential observations, and the difference in results discussed.

Guidelines for Publication of Hawai'i Journal of Health & Social Welfare Supplements

The Hawai'i Journal of Health & Social Welfare (HJH&SW) partners with organizations, university divisions, and other research units to produce topic-specific issues of the journal known as supplements. Supplements must have educational value, be useful to HJH&SW readers, and contain data not previously published elsewhere. Each supplement must have a sponsor(s) who will work with the HJH&SW staff to coordinate all steps of the process. Please contact the editors at hjhsw@hawaii.edu for more information if you would like to pursue creating a supplement.

The following are general guidelines for publication of supplements:

1. Organizations, university divisions, and other research units considering publication of a sponsored supplement should consult with the HJH&SW editorial staff to make certain the educational objectives and value of the supplement are optimized during the planning process.

2. Supplements should treat broad topics in an impartial and unbiased manner. They must have educational value, be useful to HJH&SW readership, and contain data not previously published elsewhere.

3. Supplements must have a sponsor who will act as the guest editor of the supplement. The sponsor will be responsible for every step of the publication process including development of the theme/concept, peer review, editing, preliminary copy editing (ie, proof reading and first round of copy editing), and marketing of the publication. HJH&SW staff will only be involved in layout, final copy editing and reviewing final proofs. It is important that the sponsor is aware of all steps to publication. The sponsor will:

a. Be the point of contact with HJH&SW for all issues pertaining to the supplement.

b. Solicit and curate articles for the supplement.

c. Establish and oversee a peer review process that ensures the accuracy and validity of the articles.

d. Ensure that all articles adhere to the guidelines set forth in journal's Instructions to Authors page (https://hawaiijournalhealth.org/authors.htm), especially the instructions for manuscript preparation and the statistical guidelines.

e. Obtain a signed Copyright Transfer Agreement for each article from all authors.

f. Comply with all federal, state, and local laws, rules, and regulations that may be applicable in connection with the publication, including ensuring that no protected health information appears in any article.

g. Work with the editorial staff to create and adhere to a timeline for the publication of the supplement.

h. Communicate any issues or desired changes to the HJH&SW staff in a timely manner.

4. Upon commissioning a supplement, the sponsor will be asked to establish a timeline for the issue which the sponsor and the HJH&SW editor(s) will sign. The following activities will be agreed upon with journal publication to take place no later than 24 months after signing. Extensions past the 24 months will be subject to additional fees based on journal publication rates at that time:

- Final date to submit a list of all articles, with working titles and authors
- Final date for submitting Word documents for copy editing
- Final date for submitting Word documents for layout
- Final date to request changes to page proofs (Please note that changes to page proofs will be made only to fix any errors that were introduced during layout. Other editing changes will incur an additional fee of $50 per page.)

5. The cost of publication of a HJH&SW supplement is $6,000 for an 8-article edition with an introduction from the sponsor or guest editor. Additional articles can be purchased for $500 each with a maximum of 12 articles per supplement. This cost covers one round of copy editing (up to 8 hours), layout, online publication with an accompanying press release, provision of electronic files, and indexing in PubMed Central, SCOPUS, and Embase. The layout editor will email an invoice for 50% of the supplement to the designated editor for payment upon signature of the contract. The remaining will be due at the time of publication. Checks may be made out to University Health Partners.

6. The sponsor may decide to include advertisements in the supplement in order to defray costs. Please consult with the HJH&SW advertising representative Michael Roth at 808-595-4124 or email rothcomm@gmail.com for assistance.

7. Supplement issues are posted on the HJH&SW website (https://hawaiijournalhealth.org) as a full-text PDF (both of the whole supplement as well as each article). An announcement of its availability will be made via a press release and through the HJH&SW email distribution list. Full-text versions of the articles will also be available on PubMed Central.

8. It is the responsibility of the sponsor to manage all editorial, marketing, sales, and distribution functions. If you need assistance, please contact the journal production editor. We may be able to help for an additional fee.

9. The editorial board reserves the right of final review and approval of all supplement contents. The HJH&SW will maintain the copyright of all journal contents.

Revised 3/21/23

Hawai‘i Journal of Health & Social Welfare (HJH&SW)

Style Guide for the Use of Native Hawaiian Words and Diacritical Markings

The HJH&SW encourages authors to use the appropriate diacritical markings (the ‘okina and the kahakō) for all Hawaiian words. We recommend verifying words with the Hawaiian Language Dictionary (http://www.wehewehe.org/) or with the University of Hawai‘i Hawaiian Language Online (http://www.hawaii.edu/site/info/diacritics.php).

Authors should also note that Hawaiian refers to people of Native Hawaiian descent. People who live in Hawai‘i are referred to as Hawai‘i residents.

Hawaiian words that are not proper nouns (such as *keiki* and *kūpuna*) should be written in italics throughout the manuscript, and a definition should be provided in parentheses the first time the word is used in the manuscript. Authors are encouraged to use the Hawaiian Keyboard for ‘okinas and kahakō markings. To facilitate the layout process the ‘okina should be inserted as ‘ which is the U+02BB, Modifier Letter Turned Comma mark.

Examples of Hawaiian words that may appear in the HJH&SW:

‘āina	***Mānoa***
ali‘i	***Māori***
Hawai‘i	***Moloka‘i***
kūpuna	***O‘ahu***
Kaua‘i	***‘ohana***
Lāna‘i	***Wai‘anae***

Revised 30 July 2025